



Artificial Intelligence for Wind Energy (AI4Wind): A state of the art report

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Publication date:
2019

Document Version
Publisher's PDF, also known as Version of record

[Link back to DTU Orbit](#)

Citation (APA):
Feng, J. (2019). *Artificial Intelligence for Wind Energy (AI4Wind): A state of the art report*. DTU Wind Energy E Vol. 0180

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Artificial Intelligence for Wind Energy (AI4Wind)

A state of the art report



Department of Wind Energy E Report 2019

Ju Feng

DTU Wind Energy E-0180

ISBN: 978-87-93549-48-7

February 2019

DTU Wind Energy
Department of Wind Energy



Authors: Ju Feng

Title: Artificial Intelligence for Wind Energy (AI4Wind): A state of the art report

Department: DTU Wind Energy

Summary (max 2000 characters):

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ISBN: 978-87-93549-48-7

2019

Project:

Big Data and Digitalization CCA

Sponsorship:

DTU Wind Energy

Pages: 53

Tables: 4

References: 30

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Artificial Intelligence for Wind Energy (AI4Wind)

A state of the art report

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February 15, 2019

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Abstract

This report is written for work package 3 on Artificial Intelligence in Wind Energy in the 2018 cross-cutting activity project Big Data and Digitalization, which is funded by DTU Wind Energy (Department of Wind Energy, Technical University of Denmark). In this report, the background is first introduced in Chapter 1. Chapter 2 reflects on the big picture of Artificial Intelligence. Chapter 3 reviews the state of the art of Artificial Intelligence applications in wind energy. The prospects and challenges of applying Artificial Intelligence in the wind energy sector are discussed in Chapter 4. Finally, Chapter 5 presents some conclusions.

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Preface

It is difficult to overlook Artificial Intelligence nowadays. [AlphaGo](#), self-driving cars, Google Assistant¹, face and speech recognition, ... Exciting new technologies powered by Artificial Intelligence are emerging at an astonishing pace. Companies like Baidu came out with slogans like “[All in AI](#)”. Research teams from tech giants released various open source Artificial Intelligence/Machine Learning platforms, such as [TensorFlow](#) from Google and [PyTorch](#) from Facebook. After tremendous success in various sectors, Artificial Intelligence seems to be on the track of entering into more sectors of business and society and changing our life more deeply.

How will AI change the wind energy sector? For a researcher who has worked in wind energy for several years, this is a natural question to ask. Luckily, my institute DTU Wind Energy, one of the world’s leading institutes specialized in wind energy, started an internal funded cross-cutting project on Big Data and Digitalization in 2018 and I received the opportunity to investigate the state of the art of applying Artificial Intelligence in wind energy.

This report compiles the results of the work I have done in this project and serves as the deliverable of work package 3 on Artificial Intelligence in Wind Energy. This work package is part of the 2018 cross-cutting project and focuses mainly on a state of the art review of the field. After some background introduced in Chapter 1, some reflections on the big picture of Artificial Intelligence is given in Chapter 2. Chapter 3 reviews the state of the art of Artificial Intelligence applications in wind energy. The prospects and challenges of applying Artificial Intelligence in the wind energy sector are discussed in Chapter 4. Finally, some conclusions are given in Chapter 5.

The funding from DTU Wind Energy is greatly appreciated. I also want to thank my colleagues Ignacio Martí, head of offshore wind energy programme, Nikolay Krasimirov Dimitrov, manager of the cross-cutting project, as well as those colleagues who attended the “Artificial Intelligence for Wind Energy” seminar. We had some fruitful discussions on this fascinating topic.

Specially, I would like to thank my colleague Matias Sessarego for reviewing and helping with editing of a draft of this report.

Last but not least, I want to acknowledge all the authors of the materials (books, articles, papers, reports, ...) that form the basis of this report, which I have read, reviewed, cited and quoted in this report.

Kgs. Lyngby, Denmark
Feburary, 2019

Ju Feng

¹An artificial intelligence-powered virtual assistant developed by Google that is primarily available on mobile and smart home devices.

Chapter 1

Introduction

In an online [note](#) addressed to the graduates of 2017 (Gates [2017]), Bill Gates, the founder of Microsoft, shared some of his thoughts on career advises. He wrote:

*If I were starting out today and looking for the same kind of opportunity to make a big impact in the world, I would consider three fields. One is **artificial intelligence**. We have only begun to tap into all the ways it will make people's lives more productive and creative. The second is **energy**, because making it clean, affordable, and reliable will be essential for fighting poverty and climate change. The third is the biosciences, which are ripe with opportunities to help people live longer, healthier lives.*

Among the three promising fields Gates identified, two of the them point to an exciting interplay: using Artificial Intelligence (AI) in the battle of transforming our energy sector.

Energy has long been the key backbone of modern societies. A well functioning energy sector provides crucial inputs to nearly all economic or societal activities of human beings. As the world's population and the concerns on climate change increase further, the need for a clean, affordable, and reliable energy system has become more and more urgent, as pointed out by Gates. The same need is also identified by United Nations (UN) as one of the 17 global goals for sustainable development, as shown in Fig. 1.1.



Figure 1.1: UN sustainable development goals, source: [UN foundation](#)

According to UN, the aim of Goal 7, Clean and Affordable Energy, is to “ensure access to affordable, reliable, sustainable and modern energy for all”. This goal will be achieved mainly by exploring renewable energy solutions, as UN explained on the [website](#) of global goals:

Renewable energy solutions are becoming cheaper, more reliable and more efficient every day. Our current reliance on fossil fuels is unsustainable and harmful to the planet, which is why we have to change the way we produce and consume energy. Implementing these new energy solutions as fast as possible is essential to counter climate change, one of the biggest threats to our own survival.

In its 2017 version of World Energy Outlook (IEA [2017]), International Energy Agency (IEA) identified “the rapid deployment and falling costs of clean energy technologies” as one of the four large-scale shifts in the global energy system. As the costs of renewables become cheaper, the share of renewable energy in the world’s energy mix will continue to increase. IEA projects that “Renewables capture two-thirds of global investment in power plants to 2040 as they become, for many countries, the least-costly source of new generation.” This is well evidenced since renewables contribute more to the global average annual net capacity additions than coal, gas and nuclear combined in the period 2010-2016. Of course, it is natural to expect the dominance of renewables in the newly added capacity becomes even stronger in the future. The historical and projected composition figure of annual net capacity additions in Word Energy Outlook 2017 (IEA [2017]) as shown in Fig. 1.2 confirms the expectation.

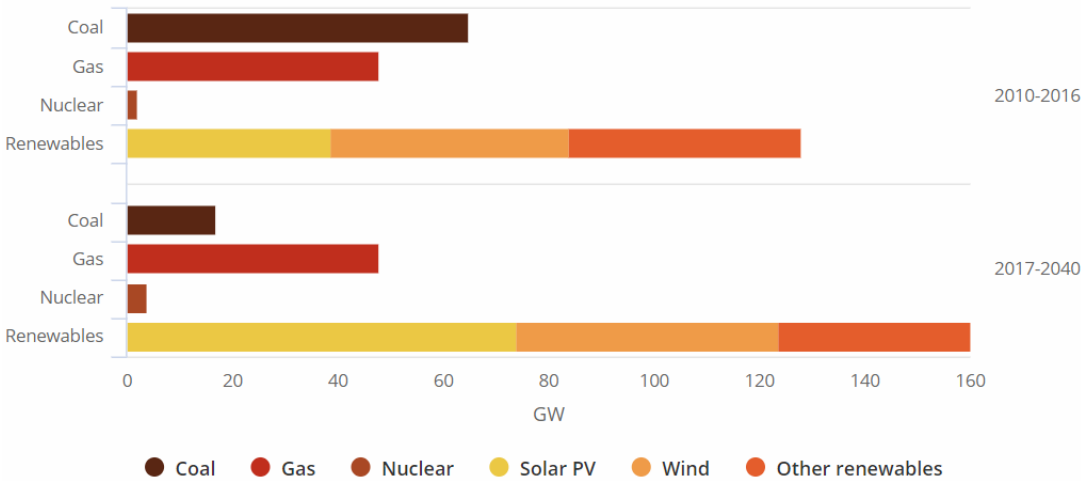


Figure 1.2: Global average annual net capacity additions by type, source: [IEA](#)

According to the latest renewable capacity highlights (IRENA [2018]) of International Renewable Energy Agency (IRENA), at the end of 2017, the total capacity of renewable energy generation in the world amounts to 2,179 GW. Among various renewable energy sources, hydro, wind and solar have the largest shares of the global total, with installed capacities of 1,152 GW, 514 GW and 397 GW, respectively (IRENA [2018]). The detailed compositions is shown in Fig. 1.3

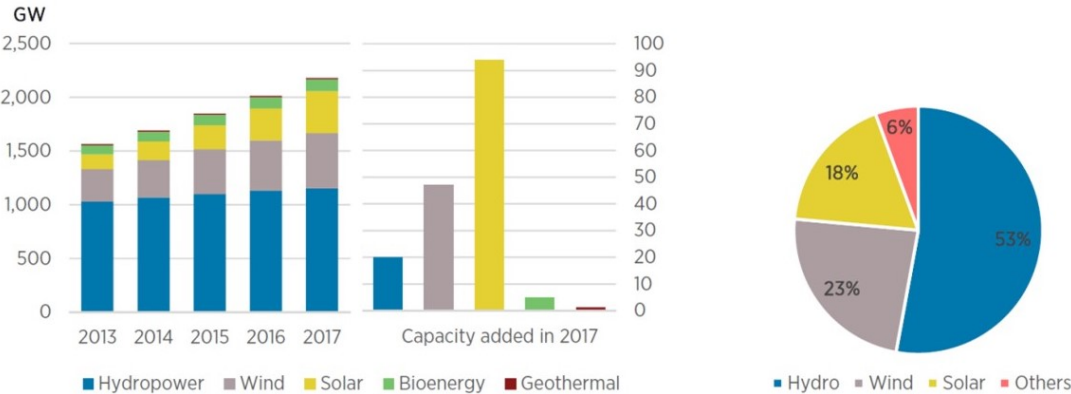


Figure 1.3: Renewable generation capacity by energy sources, source: [IRENA](#)

Clearly, the trend of increasing share of renewable energy in the world’s energy mix will continue and likely strengthen in the coming decades. While there are different types of renewable energy sources,

wind and solar will most likely be the leading two players in the newly added renewable generation capacity, as suggested by IEA’s projection.

Nevertheless, for this trend to continue and the projection made by IEA (see Fig. 1.2) to become reality, a constant improvement of renewable energy technologies and a further decrease of their cost will be required.

One way to meet this requirement that has immense potential is by use of Artificial Intelligence (AI). The potential of AI has been well identified by industries in renewable energy, especially for wind and solar. For example, in “Making renewables smarter: The benefits, risks, and future of artificial intelligence in solar and wind energy”, a [position paper](#) published in 2017 (DNV GL [2017]), DNV GL concludes:

The rate of development within artificial intelligence and its application is extremely high. For the solar and wind industries, which already have benefited from artificial intelligence applications in weather forecasting and control, the positive impact (in the relative near-term) will be on inspections and certification, with further-term impacts on supply chain and even transportation and construction. How quickly these impacts occur is an issue of debate—but they surely will occur.

This report will first reflect on the big picture of AI in Chapter 2, then examine the state of the art of AI in wind energy in Chapter 3, identify the related prospects and challenges in Chapter 4 and finally conclude with Chapter 5.

Chapter 2

AI: the big picture

2.1 The era we live in

We are living in an era in which fascinating new technologies are emerging at an astonishing pace. These new technologies, such as Internet of Things, self-driving cars, 3D printing, deep learning and quantum computing, have shown tremendous potential in transforming business and society.

In view of the fast development of these new technologies, how should we characterize this era in a historical context? Various terms or concepts have been proposed by different scholars and institutes to describe this era.

In Germany, the Industry-Science Research Alliance launched the strategic initiative “Industrie 4.0” in early 2011 and thus popularized the term “Industry 4.0” (Forschungsunion and acatech [2013]). Industry 4.0 can be viewed as the fourth industrial revolution based on Cyber-Physical Systems (CPS), while the first three industrial revolutions are results of mechanisation, electricity and IT, respectively, as shown in Fig. 2.1.

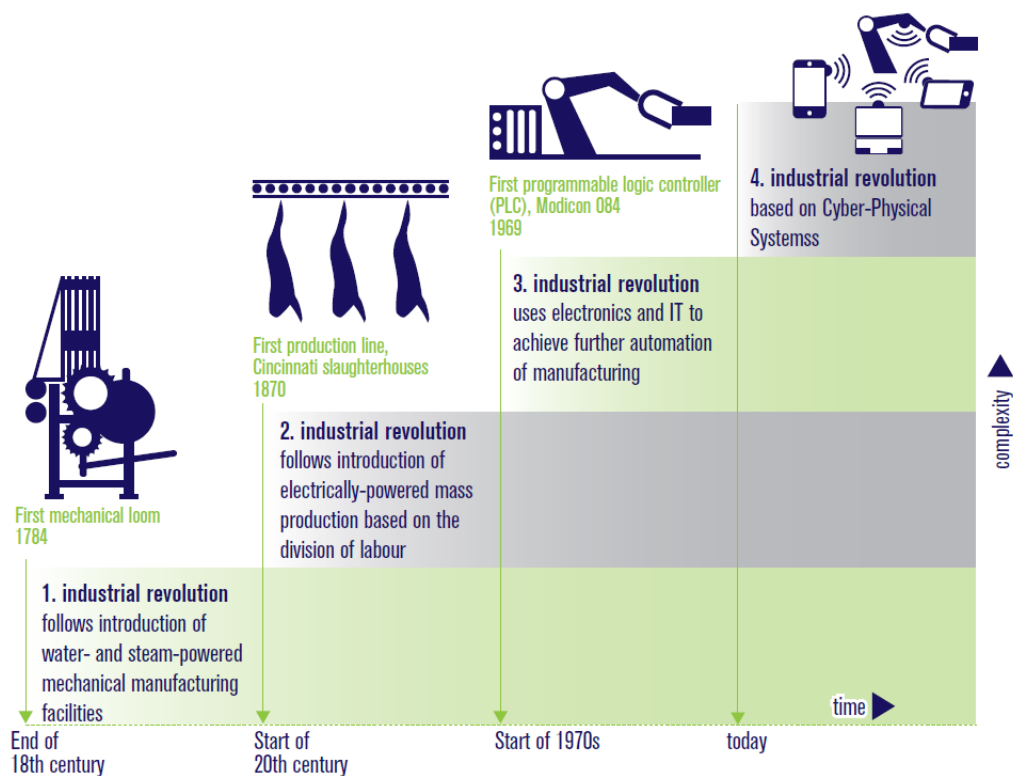


Figure 2.1: Four industrial revolutions, source: Forschungsunion and acatech [2013]

In the final report of the Industrie 4.0 Working Group (Forschungsunion and acatech [2013]), Industry 4.0 (or Industrie 4.0 in German) is defined as the product of emerging of Cyber-Physical Systems (CPS), which results from “*the convergence of the physical world and the virtual world (cyberspace)*”. In their definition, the use of Internet of Things and Services, i.e., network of resources, information, objects and people, is of central importance:

In essence, Industrie 4.0 will involve the technical integration of CPS into manufacturing and logistics and the use of the Internet of Things and Services in industrial processes. This will have implications for value creation, business models, downstream services and work organisation.

They also identified the huge potential of Industry 4.0 especially for: “*Meeting individual customer requirements; Flexibility; Optimised decision-taking; Resource productivity and efficiency; Creating value opportunities through new services; Responding to demographic change in the workplace; Work-Life-Balance; A high-wage economy that is still competitive*” (Forschungsunion and acatech [2013]).

“The Fourth Industrial Revolution” has also been used by other people and institutes to describe the current era. For example, in his recent book “The Fourth Industrial Revolution”, Klaus Schwab, the founder and executive chairman of the World Economic Forum, argued that we are now at the beginning of the fourth industrial revolution, which “*is characterized by a much more ubiquitous and mobile internet, by smaller and more powerful sensors that have become cheaper, and by artificial intelligence and machine learning*”, and also includes breakthroughs in broader areas “*ranging from gene sequencing to nanotechnology, from renewables to quantum computing*” (Schwab [2017]).

Comparing with the concept of Cyber-Physical Systems (CPS) in “Industry 4.0”, Schwab’s view cover also the biological domain as he said in the book (Schwab [2017]):

It is the fusion of these technologies and their interaction across the physical, digital and biological domains that make the fourth industrial revolution fundamentally different from previous revolutions.

Another popular term is “the second machine age”, proposed by Massachusetts Institute of Technology (MIT) Professors Erik Brynjolfsson and Andrew McAfee (Brynjolfsson and McAfee [2014]). In their 2014 book “The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies”, they argued that we are now in the second machine age when machine is replacing our mental power, whereas the first machine age initiated by the industrial revolution ¹ is represented by our physical power replaced by machine. As they stated in their book (Brynjolfsson and McAfee [2014]):

Now comes the second machine age. Computers and other digital advances are doing for mental power—the ability to use our brains to understand and shape our environments—what the steam engine and its descendants did for muscle power. They’re allowing us to blow past previous limitations and taking us into new territory. ... mental power is at least as important for progress and development—for mastering our physical and intellectual environment to get things done— as physical power. So a vast and unprecedented boost to mental power should be a great boost to humanity, just as the earlier boost to physical power so clearly was.

Unlike the two stage division of technological history proposed by Brynjolfsson and McAfee, a more detailed and systematic periodization comes from Carlota Perez, a distinguished economic historian specialized in technical change and the historical context of growth and development. She is the author of the influential book “Technological Revolutions and Financial Capital: the Dynamics of Bubbles and Golden Ages” (Perez [2002]), which focused on the role that finance plays in the diffusion of technological revolutions.

Following Austrian economist Joseph Schumpeter’s concept of “creative destruction” (Schumpeter [1942]) and theory of business cycles and development (Schumpeter [1939]), Perez analyzed the history of technological progress and economic growth in the past 250 years. Based on her research, she periodized the history into five successive technological revolutions, each of which is represented by a ‘great surge of development’. As defined in her book (Perez [2002]), a great surge of development is:

¹ This refers to the first industrial revolution began in Great Britain from around 1760, as shown in Fig. 2.1.

... the process by which a technological revolution and its paradigm propagate across the economy, leading to structural changes in production, distribution, communication and consumption as well as to profound and qualitative changes in society. The process evolves from small beginnings, in restricted sectors and geographic regions, and ends up encompassing the bulk of activities in the core country or countries and diffusing out towards further and further peripheries, depending on the capacity of the transport and communications infrastructures.

From the great surges analysis, each technological revolution is divided into an **Installation period** and **Deployment period**, split by a major crash or the so-called **Turning point**, as shown in Fig. 2.2.

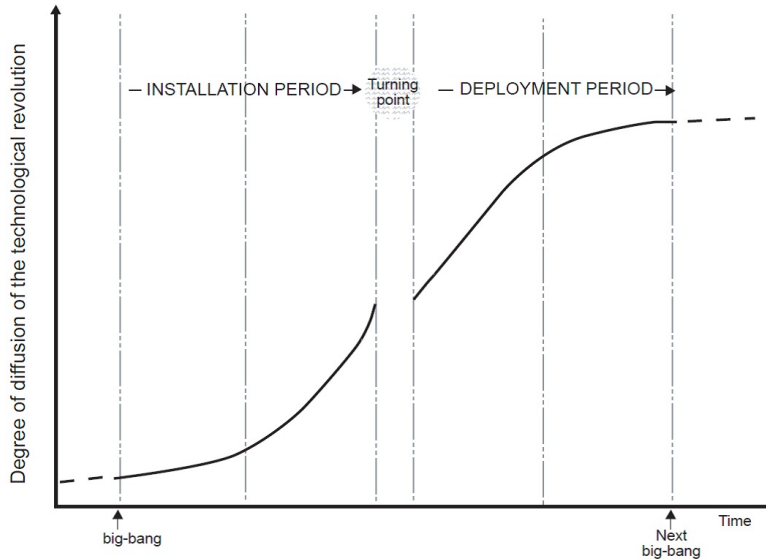


Figure 2.2: The life cycle of a great surge, source: Perez [2002]

According to Perez (Perez [2002]), these three stages can be defined as:

- **Installation period:** “the time when the new technologies irrupt in a maturing economy and advance like a bulldozer disrupting the established fabric and articulating new industrial networks, setting up new infrastructures and spreading new and superior ways of doing things. At the beginning of that period, the revolution is a small fact and a big promise; at the end, the new paradigm is a significant force, having overcome the resistance of the old paradigm and being ready to serve as propeller of widespread growth.”
- **Turning point:** “(from Installation to Deployment) is a crucial crossroads, usually a serious recession, involving a recomposition of the whole system, in particular of the regulatory context that enables the resumption of growth and the full fructification of the technological revolution.”
- **Deployment period:** “when the fabric of the whole economy is rewoven and reshaped by the modernizing power of the triumphant paradigm, which then becomes normal best practice, enabling the full unfolding of its wealth generating potential.”

Based on the above definition, Perez identified the following five technological revolutions:

- **The ‘Industrial Revolution’**, from 1771 in Britain
- **Age of Steam and Railways**, from 1829 in Britain and spread to Continent and USA
- **Age of Steel, Electricity and Heavy Engineering**, from 1875 in USA and Germany
- **Age of Oil, the Automobile and Mass Production**, from 1908 in USA, later spreading to Europe

- **Age of Information and Communications Technology (ICT)**, from 1971 in USA and spreading to Europe and Asia

These five revolutions are shown in Fig. 2.3.

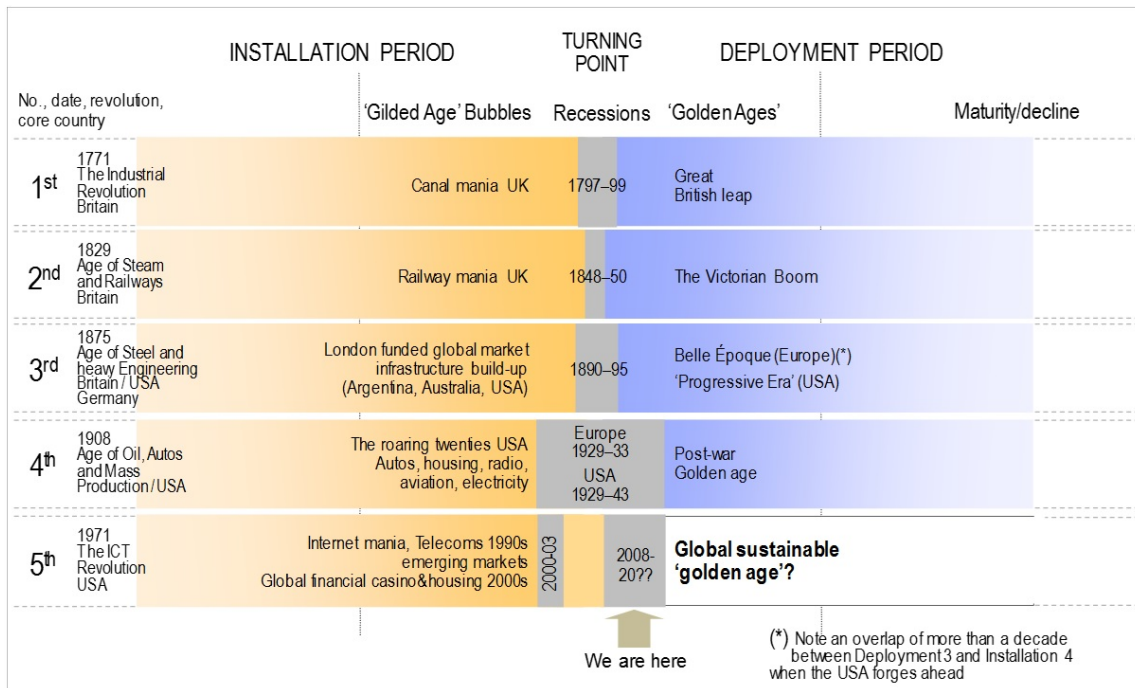


Figure 2.3: Five technological revolutions, source: [Carlota Perez](#)

According to Perez, the world today is still in the fifth technological revolution, i.e., ICT revolution, which means the current existing progresses in fields such as AI, big data, Internet of Things and self-driving cars are essentially products of the deployment stage of the ICT revolution. In this stage, the “paradigm shift” brought by the more thorough penetration of ICT technologies starts to truly transform and reshape the whole economy and society.

Based on this insight, Perez proposed the so-called “Smart Green Growth” as shown in Fig. 2.4.

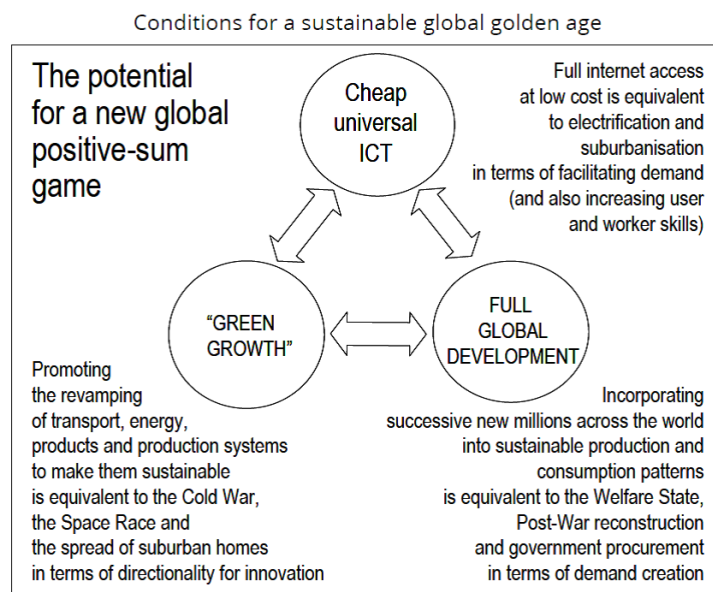


Figure 2.4: Smart green growth: a potential global positive-sum game, source: [Carlota Perez](#)

Smart green growth is a set of systematic policies Perez recommended for the world, aiming to fully unleash the potential of the ICT technological revolution while addressing the problems the world is facing now with environment, climate, and global inequality. If this direction of development is fully realized, we will enter a new global sustainable “golden age”, comparable to the postwar golden age brought by the fourth technological revolution (Perez [2017]).

Among the different views regarding our era described above, the one proposed by Perez appears the most comprehensive and systematic. The smart green growth path she recommended has already shown part of its potential in countries like Denmark where sustainability is highly valued.

2.2 The role of AI

No matter which term is used to describe the era we are living in, being it ‘The Second Machine Age’, ‘The Fourth Industrial Revolution’ or ‘The Fifth Technological Revolutions’, one core technology that holds tremendous potential in transforming nearly all aspects of our economy, society and life is AI. This becomes increasingly evident in recent years when universal digitalization, ubiquitous connectivity, and ever-cheaper data storage capacity allow AI technologies start to reach their full potentials.

Similar conclusion on AI has also been reached by many other researchers and institutes.

In a 2013 report entitled “Disruptive technologies: Advances that will transform life, business, and the global economy”, McKinsey Global Institute identified twelve technologies that they believe “have significant potential to drive economic impact and disruption by 2025” (McKinsey Global Institute [2013]). These twelve technologies and their estimated potential economics impacts are shown in Fig. 2.5.

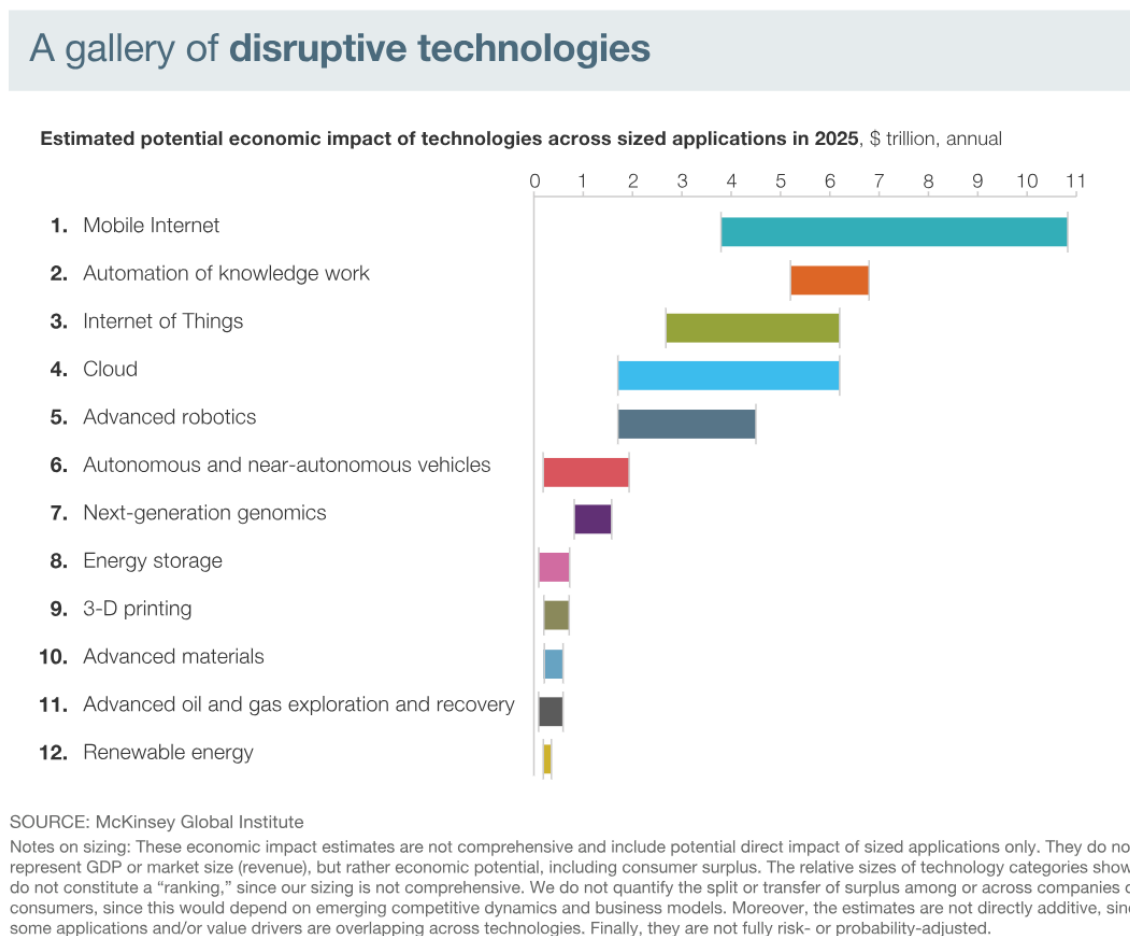


Figure 2.5: Twelve disruptive technologies identified in 2013, source: [McKinsey Global Institute](#)

The first six technologies shown in Fig. 2.5 can actually be classified into the general term of ICT

technologies, while ICT technologies are also likely to play important roles in the remaining six technologies. The second disruptive technology, i.e., “Automation of knowledge work” is especially relevant for the discussion of AI, as stated in the executive summary of this report:

Advances in artificial intelligence, machine learning, and natural user interfaces (e.g., voice recognition) are making it possible to automate many knowledge worker tasks that have long been regarded as impossible or impractical for machines to perform. For instance, some computers can answer “unstructured” questions (i.e., those posed in ordinary language, rather than precisely written as software queries), so employees or customers without specialized training can get information on their own. This opens up possibilities for sweeping change in how knowledge work is organized and performed. Sophisticated analytics tools can be used to augment the talents of highly skilled employees, and as more knowledge worker tasks can be done by machine, it is also possible that some types of jobs could become fully automated.

Clearly, this definition echoes well with Brynjolfsson and McAfee’s idea of ‘Second Machine age’ in which machines replace our mental power. In a more general manner, “Automation of knowledge work” can also be viewed as the application of AI technologies. The key applications identified by McKinsey Global Institute include:

- Smart learning in education
- Diagnostics and drug discovery in health care
- Discovery, contracts/patents in legal sector
- Investments and accounting in finance sector

Of course, the above list is far from comprehensive. AI technologies hold huge potential for nearly all sectors in our economy and business. This is also true for the energy sector, in which renewable energy sources such as wind and solar are transforming the landscape of the world energy system and benefiting from AI. Nowadays, digitalization is occurring in the whole process of energy use for our world, from extracting, storing, transporting to utilizing energy. Digitalization essentially has settled the playground for AI technologies to realize their promising benefits for making a new generation energy system that is sustainable, smart, flexible and reliable.

2.3 The story of AI

The birth of AI is commonly dated back to 1956. During the summer of 1956, a two-month workshop was organized at Dartmouth College in Hanover, New Hampshire, USA by John McCarthy, Marvin Minsky, and eight other researchers who would later become the pioneers in the field of AI (Russell and Norvig [2010]). In the original proposal for this workshop, where the term “Artificial Intelligence” was first used, McCarthy et al. (McCarthy et al. [1955]) stated:

*We propose that a 2 month, 10 man study of **artificial intelligence** be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.*

Following the Dartmouth workshop, the field of AI has received great enthusiasm and expectations, also generous public funding for around 20 years. In this early stage, AI researchers have made some bold predictions, such as the one made by Herbert Simon in 1957 (Russell and Norvig [2010]):

It is not my aim to surprise or shock you—but the simplest way I can summarize is to say that there are now in the world machines that think, that learn and that create. Moreover,

their ability to do these things is going to increase rapidly until—in a visible future—the range of problems they can handle will be coextensive with the range to which the human mind has been applied.

Although large progresses have been made for idealized problems in a small scale, AI failed to meet the great expectations and solve realistic problems in a large scale. This failure also results in the so-called AI winter, when governments stopped to fund AI research. Since then, the field of AI has gone through several periods of ups and downs. Quite recently, AI has become a popular area again with slogans such as “AI in all” or “All in AI” emerge. This round of AI success can be largely attributed to the now highly increased computation capacity, large amount of data and thus successful applications of Machine Learning in many real-life problems.

In the first chapter of his book published in 2011, “Introduction to Artificial Intelligence”, Wolfgang Ertel (Ertel [2011]) made a detailed list of milestones in the development of AI from 1931 to 2011, which are copied here as follows:

- **1931** The Austrian Kurt Gödel shows that in first-order predicate logic all true statements are derivable. In higher-order logics, on the other hand, there are true statements that are unprovable.
- **1937** Alan Turing points out the limits of intelligent machines with the halting problem.
- **1943** McCulloch and Pitts model neural networks and make the connection to propositional logic.
- **1950** Alan Turing defines machine intelligence with the Turing test and writes about learning machines and genetic algorithms.
- **1951** Marvin Minsky develops a neural network machine. With 3000 vacuum tubes he simulates 40 neurons.
- **1955** Arthur Samuel (IBM) builds a learning chess program that plays better than its developer.
- **1956** McCarthy organizes a conference in Dartmouth College. Here the name Artificial Intelligence was first introduced. Newell and Simon of Carnegie Mellon University (CMU) present the Logic Theorist, the first symbol-processing computer program.
- **1958** McCarthy invents at MIT (Massachusetts Institute of Technology) the high-level language LISP. He writes programs that are capable of modifying themselves.
- **1959** Gelernter (IBM) builds the Geometry Theorem Prover.
- **1961** The General Problem Solver (GPS) by Newell and Simon imitates human thought.
- **1963** McCarthy founds the AI Lab at Stanford University.
- **1965** Robinson invents the resolution calculus for predicate logic.
- **1966** Weizenbaum’s program Eliza carries out dialog with people in natural language.
- **1969** Minsky and Papert show in their book Perceptrons that the perceptron, a very simple neural network, can only represent linear functions.
- **1972** French scientist Alain Colmerauer invents the logic programming language PROLOG. British physician de Dombal develops an expert system for diagnosis of acute abdominal pain. It goes unnoticed in the mainstream AI community of the time.
- **1976** Shortliffe and Buchanan develop MYCIN, an expert system for diagnosis of infectious diseases, which is capable of dealing with uncertainty.
- **1981** Japan begins, at great expense, the “Fifth Generation Project” with the goal of building a powerful PROLOG machine.
- **1982** R1, the expert system for configuring computers, saves Digital Equipment Corporation 40 million dollars per year.

- **1986** Renaissance of neural networks through, among others, Rumelhart, Hinton and Sejnowski. The system Nettetalk learns to read texts aloud.
- **1990** Pearl, Cheeseman, Whittaker, Spiegelhalter bring probability theory into AI with Bayesian networks. Multi-agent systems become popular.
- **1992** Tesauros TD-gammon program demonstrates the advantages of reinforcement learning.
- **1993** Worldwide RoboCup initiative to build soccer-playing autonomous robots.
- **1995** From statistical learning theory, Vapnik develops support vector machines, which are very important today.
- **1997** IBM's chess computer Deep Blue defeats the chess world champion Gary Kasparov. First international RoboCup competition in Japan.
- **2003** The robots in RoboCup demonstrate impressively what AI and robotics are capable of achieving.
- **2006** Service robotics becomes a major AI research area.
- **2010** Autonomous robots start learning their policies.
- **2011** IBM's natural language understanding and question answering program "Watson" defeats two human champions in the U.S. television quiz show "Jeopardy!".

Fig. 2.6 from SYZYGY (SYZYGY [2017]) illustrates a concise and updated time line of the development AI. Note that in this figure, the birth of AI is dated back to 1955, when McCarthy et al. wrote the original proposal for the AI workshop and the term "Artificial Intelligence" was first used (McCarthy et al. [1955]).

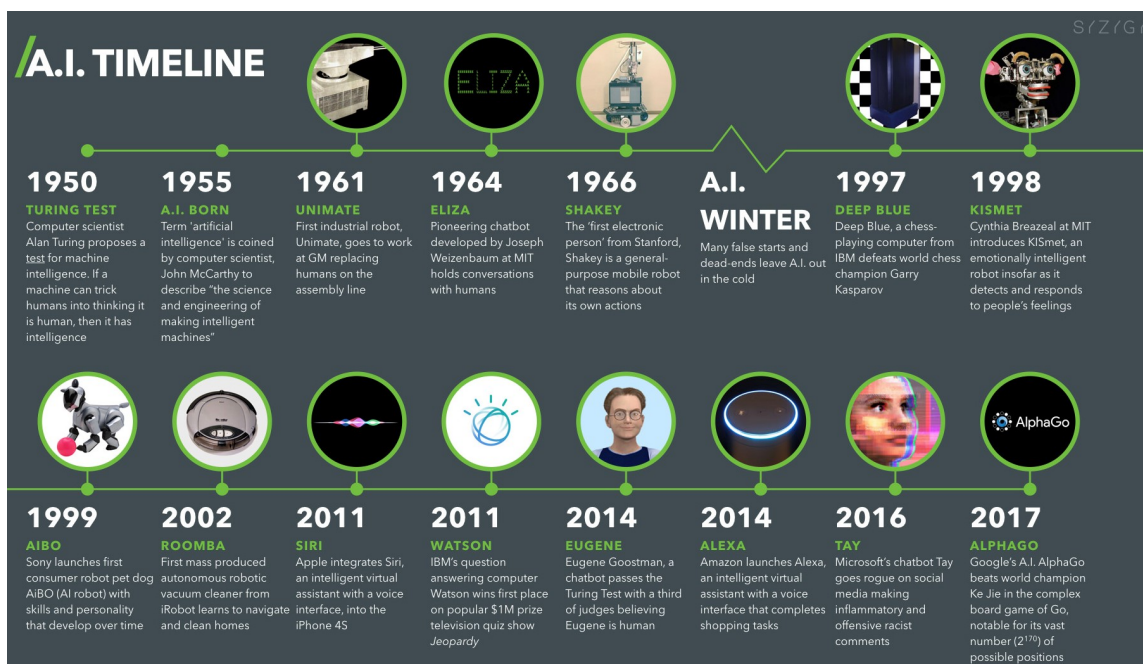


Figure 2.6: AI timeline, source: SYZYGY

For a more detailed history of AI, one could consult the relevant chapters of the books referred above (Russell and Norvig [2010], Ertel [2011]) or the historical book on AI by Pamela McCorduck (McCorduck [2004]).

2.4 AI, Machine Learning and Big Data

What is AI? This is not a trivial question to answer as there is no standard definition of the term Artificial Intelligence. According to the book by Ertel (Ertel [2011]), the first definition of AI was given by John McCarthy roughly as follows:

The goal of AI is to develop machines that behave as though they were intelligent.

Apparently this definition leaves a large space for interpretation regarding what it means to behave intelligently, therefore it is not so applicable for real-life applications.

In one of the most widely used textbook on AI (Russell and Norvig [2010]), Russel and Norvig collected eight definitions of AI and classified them into four categories, as shown in Fig. 2.7.

Thinking Humanly “The exciting new effort to make computers think . . . <i>machines with minds</i> , in the full and literal sense.” (Haugeland, 1985) “[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning . . .” (Bellman, 1978)	Thinking Rationally “The study of mental faculties through the use of computational models.” (Charniak and McDermott, 1985) “The study of the computations that make it possible to perceive, reason, and act.” (Winston, 1992)
Acting Humanly “The art of creating machines that perform functions that require intelligence when performed by people.” (Kurzweil, 1990) “The study of how to make computers do things at which, at the moment, people are better.” (Rich and Knight, 1991)	Acting Rationally “Computational Intelligence is the study of the design of intelligent agents.” (Poole <i>et al.</i> , 1998) “AI . . . is concerned with intelligent behavior in artifacts.” (Nilsson, 1998)

Figure 2.7: Some definitions of AI organized into four categories, source: Russell and Norvig [2010]

They explained their classification in their book as follows:

The definitions on top are concerned with thought processes and reasoning, whereas the ones on the bottom address behavior. The definitions on the left measure success in terms of fidelity to human performance, whereas the ones on the right measure against an ideal performance measure, called rationality. A system is rational if it does the “right thing,” given what it knows.

Russel and Norvig adopted the “acting rationally” approach in their book, which they called as “the rational agent approach”. The rational agent approach is also the most workable definition as it avoids the complicated task of defining what is thinking and what it means to be humanly, given the fact that we are still far from scientifically understanding human mind and intelligence.

In Russel and Norvig’s definition, an agent is “just something that acts”, which is also expected to “operate autonomously, perceive their environment, persist over a prolonged time period, adapt to change, and create and pursue goals.” Thus a rational agent is an agent that “acts so as to achieve the best outcome or, when there is uncertainty, the best expected outcome.”

For example, a rational agent can have a model of “how the world works” in the agent’s context and a utility function to measure how good is the outcome from its acts. This example is the so-called “model-based, utility-based agent” and is shown in Fig. 2.8.

According to this definition, many fields can be recognized as applications of AI. For example, in a recent textbook published in 2016, “Introduction to Artificial Intelligence”, Mariusz Flasiński (Flasiński [2016]) discussed the following application areas:

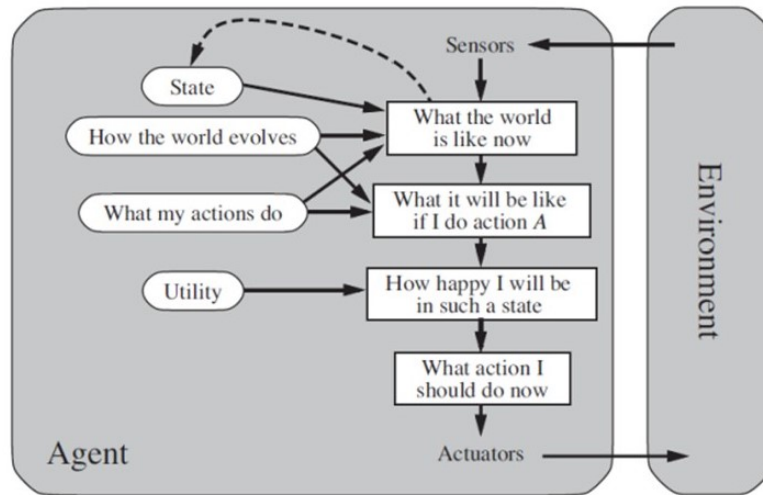


Figure 2.8: A model-based, utility-based agent, source: Russell and Norvig [2010]

- Perception and Pattern Recognition
- Knowledge Representation
- Problem Solving
- Reasoning
- Decision Making
- Planning
- Learning
- Natural Language Processing (NLP)
- Manipulation and Locomotion
- Social Intelligence, Emotional Intelligence and Creativity

Of course, this list can never be complete and static, since the scope of AI has been changing constantly. Actually, there is a phenomenon known as “[AI effect](#)”, which describes that as soon as AI achieves something, that something tends to become regarded as not AI. As Pamela McCorduck puts in her book on history of AI (McCorduck [2004]):

It’s part of the history of the field of artificial intelligence that every time somebody figured out how to make a computer do something—play good checkers, solve simple but relatively informal problems—there was chorus of critics to say, “that’s not thinking”.

Kevin Kelly, the founding executive editor of Wired magazine, also wrote in a Wired article in 2014 (Kelly [2014]):

In the past, we would have said only a superintelligent AI could drive a car, or beat a human at Jeopardy! or chess. But once AI did each of those things, we considered that achievement obviously mechanical and hardly worth the label of true intelligence. Every success in AI redefines it.

Thus, according to Douglas Hofstadter’s quotation of Tesler (Hofstadter [1979]), AI is “whatever hasn’t been done yet”. Of course, this distinction, i.e., regarding those have been done as not AI while those haven’t been done as AI, is not so useful, as it defines AI as a target that we can never meet.

In view of this, Katherine Bailey proposed in a 2016 [article](#) (Bailey [2016]) a different distinction as shown in Fig. 2.9.

To understand this distinction, the classification of AI into weak and strong AI is explained as follows:

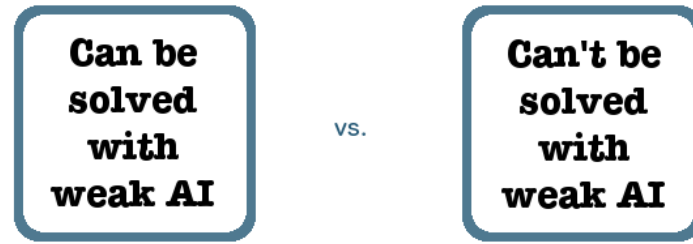


Figure 2.9: A more useful distinction for AI effect, source: Bailey [2016]

- **Weak AI:** machines could possibly behave intelligently.
- **Strong AI:** such machines would count as having actual minds (as opposed to simulated minds).

A similar classification that focuses on the application is narrow and general AI, which can be described as:

- **Narrow AI:** a machine with the ability to apply intelligence to only specific problems.
- **General AI:** a machine with the ability to apply intelligence to any problem.

Clearly the rational agent approach adopted by Russel and Norvig (Russell and Norvig [2010]) belongs to weak and narrow AI, as this approach focuses on “acting rationally” and currently a rational agent can only be well defined for specific application fields.

After examining some successful applications of AI until nowadays, from self-driving cars to AlphaGo, we can confidently conclude that we are still very far away from the strong and general AI. This is also a conclusion that most AI researchers and practitioners would agree. Thus, the popular fear in typical scientific fictions and mass media nowadays that a super-intelligent AI will gain consciousness and take over the world is unfounded, at least for the foreseeable future.

Besides AI, there are two other buzz words as popular as AI, which are “Machine Learning” and “Big Data”. How are these three terms related? The best answer is given by Andrew Ng in the rocket metaphor as shown in Fig. 2.10.

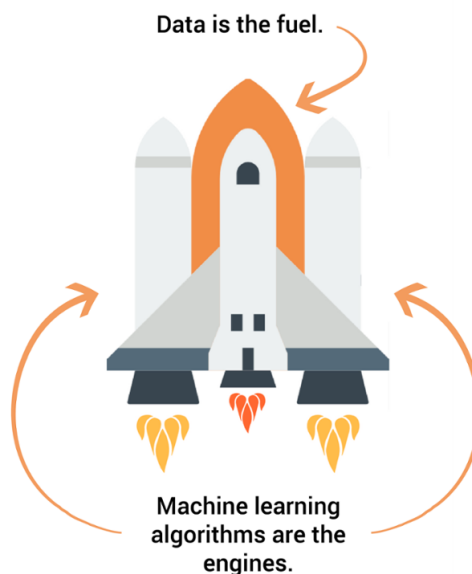


Figure 2.10: The AI rocket metaphor by Andrew Ng, source: [link](#)

Andrew Ng, former VP and Chief Scientist at Baidu, co-founder of Coursera, and adjunct professor at Stanford University, is one of the most famous AI researchers in recent years. He once described the relationship between AI, Machine Learning and Big Data as follows:

AI is akin to building a rocket ship. You need a huge engine and a lot of fuel. The rocket engine is the learning algorithms but the fuel is the huge amounts of data we can feed to these algorithms.

According to this metaphor, AI's success largely relies on the advancement of Machine Learning algorithms and the huge amounts of data, i.e., so-called Big Data. Similar conclusion has also been reached by Kevin Kelly in his 2014 article entitled "The three breakthroughs that have finally unleashed AI on the World" (Kelly [2014]). The three recent breakthroughs he identified that have unleashed the long-awaited arrival of AI are:

- **Cheap parallel computation** (especially clusters of GPUs that enable running neural networks in parallel)
- **Big Data** (massive databases, self-tracking, web cookies, online footprints, terabytes of storage, decades of search results, Wikipedia, and the entire digital universe)
- **Better algorithms** (such as deep learning algorithms)

As defined in by Tom Mitchell (Mitchell [1997]), Machine Learning is "*the study of computer algorithms that improve automatically through experience*", which can be viewed as a sub field of AI. The relationship between AI, Machine Learning and Deep Learning can be described in the diagram in Fig. 2.11, while Big Data can be viewed as essential inputs to these technologies.

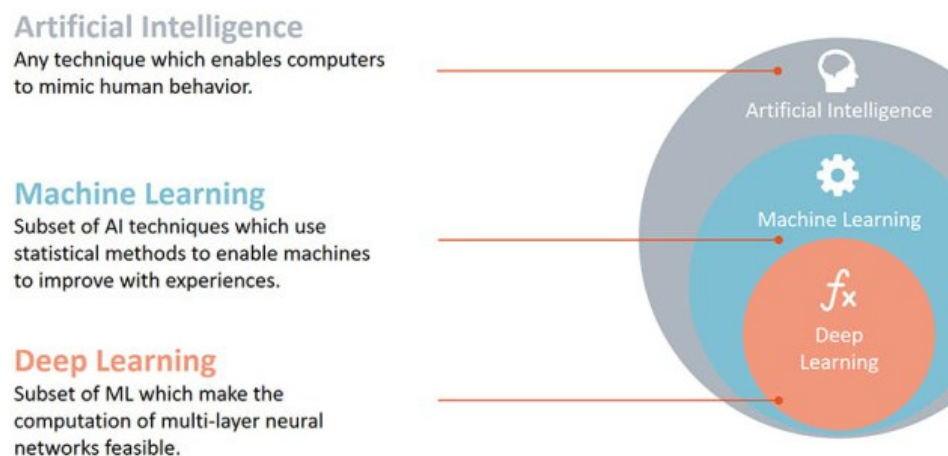


Figure 2.11: Relationship between AI, Machine Learning and Deep Learning, source: [KDnuggets](#)

In general, Machine Learning algorithms can be classified into three categories (Russell and Norvig [2010]):

- **Supervised Learning:** the agent observes some example input–output pairs and learns a function that maps from input to output.
- **Unsupervised learning:** the agent learns patterns in the input even though no explicit feedback is supplied.
- **Reinforcement learning:** the agent learns from a series of reinforcements — rewards or punishments.

Currently, the most widely used and mature machine learning techniques belong mainly to the category of supervised learning. Thus, current machine learning is best at A to B mapping.

In the [position paper](#) published in 2017 (DNV GL [2017]), DNV GL listed five common supervised learning algorithms and three common unsupervised learning algorithms in two figures, which are copied here in Figs. 2.12 and 2.13.

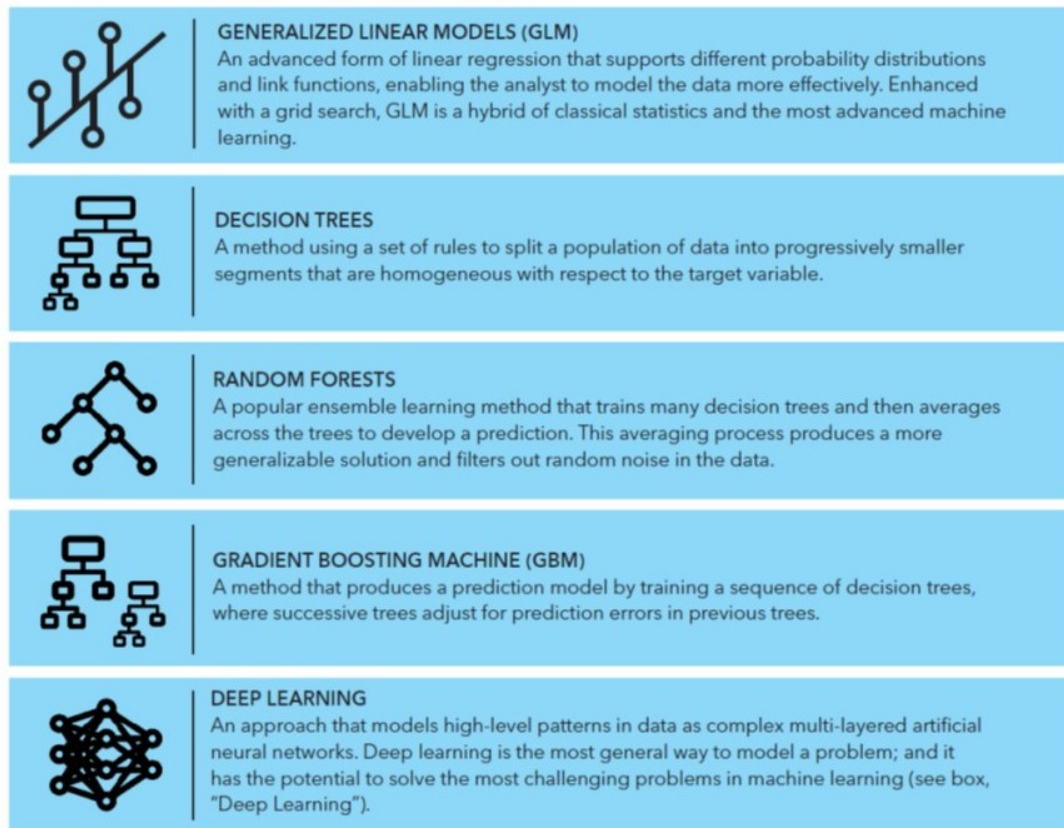


Figure 2.12: Five common supervised learning algorithms, source: DNV GL [2017]

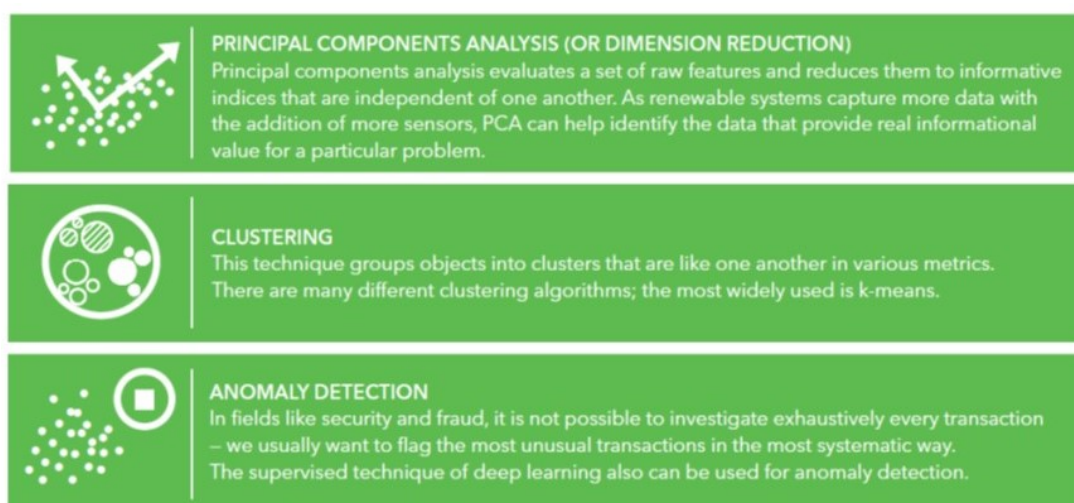


Figure 2.13: Three common unsupervised learning algorithms, source: DNV GL [2017]

2.5 Challenges of AI

In recent years, AI has demonstrated its potential in various successful stories and attracted tremendous interest among researchers, entrepreneurs, government officials, and also citizens who have increasingly benefited from the applications of AI.

Nevertheless, AI's further success will encounter many challenges in the future. One challenge comes from society's fear of a super intelligent AI which (who) will take control over the world, although this fear is unfounded. Other challenges are largely due to its lack of rigorous theoretical basis if compared with more mature scientific disciplines such as physics. The lack of rigorous theoretical basis will likely show stronger effects when AI moves further into safety or health crucial application fields.

Examining the current successful applications of AI (mainly ML), we find two facets:

- **The beautiful facet:** it works well!
- **The scary facet:** we hardly know why it works!

There is a view that ML (or AI) has become a form of “alchemy”, proposed by Ali Rahimi in a speech² given in NIPS 2017. Note that NIPS, i.e., Conference on Neural Information Processing Systems, is one of the most prestigious AI conferences held annually.

As described by Matthew Hutson in an [article](#) in Science Magazine, “AI researchers allege that machine learning is alchemy” (Hutson [2018a]):

Speaking at an AI conference, Ali Rahimi charged that machine learning algorithms ... have become a form of “alchemy.” Researchers, he said, do not know why some algorithms work and others don't, nor do they have rigorous criteria for choosing one AI architecture over another.

A different view held by another famous AI researcher, Yann Lecun, is that AI is engineering. As Mathew Hutson put in the same article:

Yann LeCun, Facebook's chief AI scientist in New York City, worries that shifting too much effort away from bleeding-edge techniques toward core understanding could slow innovation and discourage AI's real-world adoption. “It's not alchemy, it's engineering,” he says. “Engineering is messy.”

While whichever of these two views is more correct is up for discussion, one of the fundamental limitations of the current AI/ML techniques is undeniable: the lack or the insufficiency of interpretability. As stated in an article “Is Artificial Intelligence Permanently Inscrutable?” (Bornstein [2016]):

Modern learning algorithms show a trade-off between human interpretability, or explainability, and their accuracy. Deep learning is both the most accurate and the least interpretable.

Bornstein also showed this trade-off for some widely used AI/ML techniques in a figure, as copied here in Fig. 2.14.

The problem of interpretability also shows in the challenges brought by the so called “adversarial examples”. Adversarial examples are inputs/examples deliberately formed by applying small but intentionally worst-case perturbations to some otherwise normal examples. These examples can fool many ML models including deep learning models and lead the models output an incorrect answer with high confidence (Goodfellow et al. [2014]). One of such example is shown in Fig. 2.15.

²The speech can be found on YouTube: <https://www.youtube.com/watch?v=x7psGHgatGM>

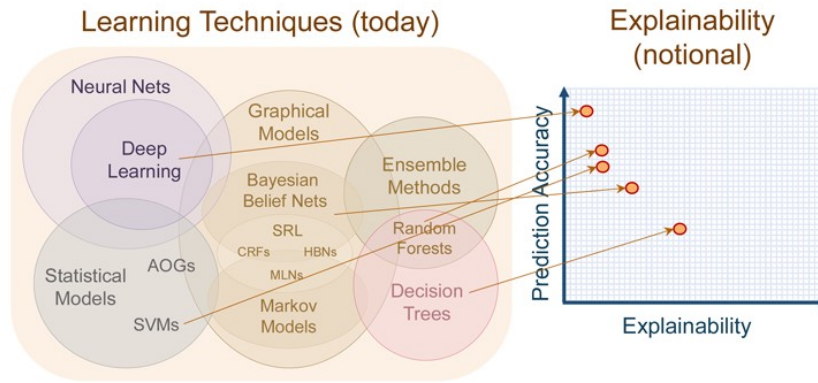


Figure 2.14: Explainability vs. prediction accuracy for different AI/ML techniques, source: Bornstein [2016]

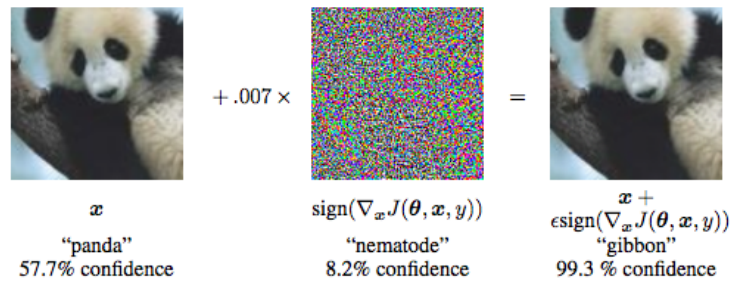


Figure 2.15: A normal picture of panda when added specifically added noise is classified as a gibbon by a neural network (GoogLeNet), source: Goodfellow et al. [2014]

More adversarial examples as included in a recent article published in the Science magazine, “Hackers easily fool artificial intelligences” (Hutson [2018b]), are shown in Fig. 2.16.



Figure 2.16: More adversarial examples , source: Hutson [2018b]

Apparently this kind of vulnerability puts serious security concerns when applying AI/ML techniques to certain fields, as have been addressed in the article mentioned above (Hutson [2018b]).

In a recent UC Berkeley article (Geng and Veerapaneni [2018]), “Tricking Neural Networks: Create

your own Adversarial Examples”, Daniel Geng and Rishi Veerapaneni compared adversarial examples to a common human phenomenon, optical illusions:

You can understand adversarial examples by thinking of them as optical illusions for neural networks. In the same way optical illusions can trick the human brain, adversarial examples can trick neural networks.

Of course, the possibility of tricking some of the state-of-the-art AI/ML models by intentionally made adversarial examples reminds us that our understandings of AI/ML methods are still very limited. The limitations of AI and the possible attacks it might encounter must be carefully studied before an AI/ML system is used in some critical real-life applications. As concluded by Daniel Geng and Rishi Veerapaneni in the above mentioned article (Geng and Veerapaneni [2018]):

*As we move toward a future that incorporates more and more neural networks and deep learning algorithms in our daily lives we have to be careful to remember that these models can be fooled very easily. Despite the fact that neural networks are to some extent biologically inspired and have near (or super) human capabilities in a wide variety of tasks, adversarial examples teach us that their method of operation is nothing like how real biological creatures work. As we’ve seen neural networks can fail quite easily and catastrophically, in ways that are completely alien to us humans. ... **All in all, adversarial examples should humble us. They show us that although we have made great leaps and bounds there is still much that we do not know.***

Chapter 3

AI4Wind: the state of the art

Bringing AI to the field of wind energy is not a new idea. Back in 1985, McAnulty reviewed the possible application of AI (also called as expert systems in the article) to wind power problem, in a paper entitled “The next generation - intelligent wind mills?” (McAnulty [1985]). In the introduction section of the paper, McAnulty wrote:

Both wind energy and artificial intelligence are fairly trendy topics, with AI slightly ahead at the moment. Could it be that, besides their shared trendiness, they might have some deeper relationship? Time will tell, of course, but I would like to draw attention to a few ideas that could prompt further investigation.

In this paper, McAnulty made the distinction of “strong AI” and “weak AI”, identified the need of “vast amounts of data”, and described two ways of dealing with uncertainty: “Bayesian statistics” and “Fuzzy set theory”. The potential applications for weak AI in wind energy that he suggested include: “fault diagnosis”, “site/machine type selection” and “maintenance scheduling”. Looking from more than three decades later, we can conclude that McAnulty had made a quite precise prediction regarding the future of AI4Wind (Artificial Intelligence for Wind Energy), maybe just too ahead of the time in a certain degree.

While after 1985 wind energy has gone through stages of rapid development and merged as one of the crucial players in the world’s energy mix, AI has experienced a relatively silent period. But as discussed in the previous chapter, AI has now become a trendy topic in recent years and gained tremendous momentum and interest again.

Nevertheless, the application of AI in wind energy field has been studied in a huge amount of literature and also successfully demonstrated in various industrial cases. It is also likely that AI4Wind is going to receive even more attention and bring various benefits for the further development and deployment of wind energy.

In this chapter, the state of the art in AI4Wind will be reviewed, by first analyzing the published papers with the highest impacts, and then describing two successful industrial cases.

3.1 Literature review

To find the relevant literature on AI4Wind, Scopus is used, which is “the largest abstract and citation database of peer-reviewed literature: scientific journals, books and conference proceedings”. A programmatic approach is employed to search the database and find the relevant literature, based on an open source Python-based API-Wrapper (API stands for application programming interface) to access Scopus. This tool can be found at: <https://github.com/scopus-api/scopus>.

Using the tool mentioned above, a Python script is written to search the Scopus database through queries with specified keywords, which are chosen to cover the field of AI4Wind. After this, a large amount of papers are found. However, among these found papers there are mismatches, i.e., papers that don’t really deal with AI4Wind. On the other hand, the found papers are far from being comprehensive,

since it is impossible to find all papers in AI4Wind, as there is no combination of keywords that can do this perfectly.

After retrieving the information (including title, author, journal/conference title, year, citation count, abstract, etc.) of the AI4Wind papers, a threshold on average citation per year is set to find the papers with high impact. Note that the average citations per year is chosen as a convenient metric to measure impact, not because it is the best way but because it is an objective and quantitative way. When calculating the average citations per year, the month that a paper is published is considered by counting one month as 1/12 year. To exclude those “false positives”, i.e., papers that matches the keywords criterion and citation threshold but are not in the field of AI4Wind, a manual examination is done by checking the title and abstract of each paper. After this step, the highly cited AI4Wind papers are selected. The whole process can be shown in flowchart in Fig. 3.1.

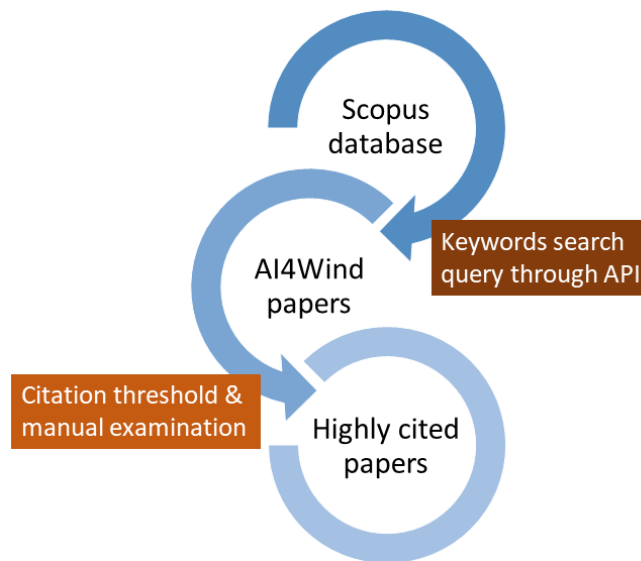


Figure 3.1: The process of selecting focused papers

The keyword criterion and citation threshold for finding the papers are listed in Table 3.1.

Table 3.1: Selection of highly cited AI4Wind papers

Papers on AI4Wind (based on Scopus search through API @ March 21, 2018)	
Criterion	Title(wind) and Title-Abs-Key(intelligence or neural or ANN or AI or learning or data mining or big data)
Total	4172 (there are false positive and false negative)
Highly cited	288 (≥ 5 citations per year since publication according to Scopus)

Out of 4172 AI4Wind papers, 288 papers are selected as highly cited ones. The complete list of these 288 papers can be found in Appendix. Note that the selection of these papers is done based on data retrieved from Scopus on March 21, 2018. The number of highly cited AI4Wind papers by year is shown in Fig. 3.2.

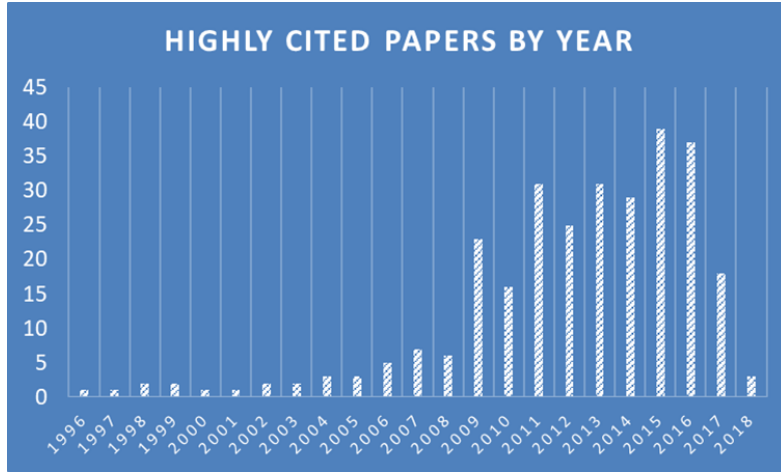


Figure 3.2: Highly cited AI4Wind papers by year

What kind of applications do these highly cited papers focus on? To answer this question, a text mining study is first carried out. For this purpose, a popular Python library for natural language processing, `nltk` (natural language toolkit) is used.

Based on the text of titles and abstracts of the 4172 AI4Wind papers, a word cloud which plots the 20 most frequent words is shown in Fig. 3.3.

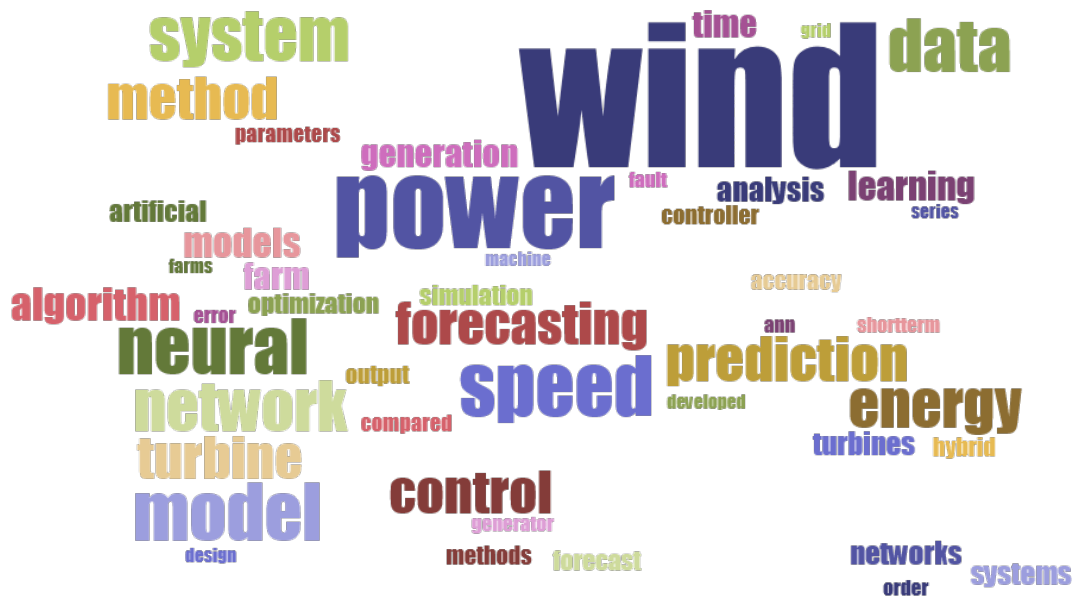


Figure 3.3: Most frequent words in the titles and abstracts of the 4172 AI4Wind papers

Note that the size of a word is proportional to its frequency in the text, and common words that don't carry domain specific meanings, so-called "stop words" (such as "the", "is", "and") in natural language processing, have been filtered out. The word cloud figure is generated at: <https://www.jasondavies.com/wordcloud/>.

Similar word cloud figure based on the titles and abstracts of the 288 highly cited AI4Wind papers is shown in Fig. 3.4.

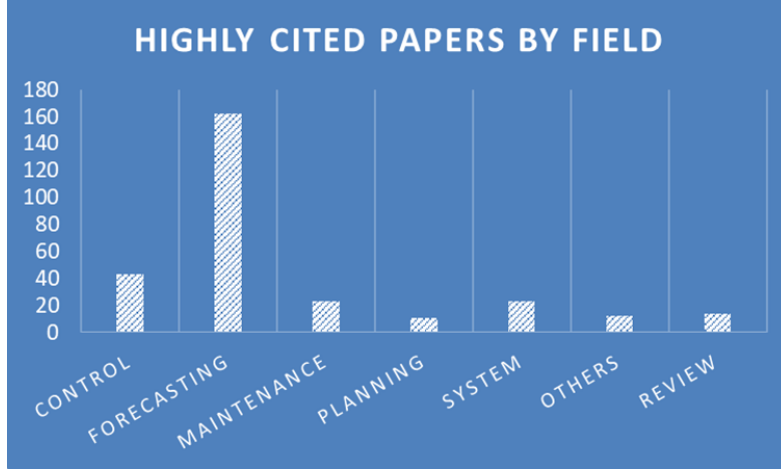


Figure 3.5: Highly cited AI4Wind papers by field

Among the 288 papers, the paper with most citations per year is an review article from *Renewable Energy*. This paper was entitled “Current methods and advances in forecasting of wind power generation” and reviewed the field of wind power forecasting (Foley et al. [2012]). Since its publication in 2011, it has received 414 citations until March 21, 2018, i.e., 66.24 citations per year.

According to this paper, wind power forecasting models can be classified as two groups: one is NWP (numerical weather prediction) based and the other uses statistical and machine learning techniques. In the second group, various AI/ML techniques, such as various kinds of ANNs, SVM (support vector machine) and FIS (fuzzy inference system), have demonstrated the benefits of using AI in wind power forecasting (Foley et al. [2012]).

Excluding those review articles, the paper receives highest citations per year is “Optimal energy storage sizing and control for wind power applications” (Brekken et al. [2011]), which was published in 2011 in *IEEE Transactions on Sustainable Energy* and received 35.03 citations per year on average.

In this paper, the inclusion of large scale energy storage (a zinc/bromine flow battery-based system) to improve the predictability of wind power was investigated. It was demonstrated that effective control and coordination of energy storage system can make sure that the wind farm output lies in a tight range (4%) around the forecasted value in 90% of the time, which will help utilities to decrease their spinning reserve requirements and lower the cost of integrating more wind power. Among four control strategies considered, the advanced ANN controller is found to perform best. For this controller, a three layer ANN is trained with a genetic algorithm, with three inputs: forecasted and actual wind farm output power, energy storage state of charge, and one output: commended energy storage power. Note that the output determines the control strategy of the energy storage system.

Analyzing the authors’ information of the 288 highly cited papers, we can find the institutes that have published more than five highly cited papers as listed in Table 3.2.

Table 3.2: Institutes with more than five highly cited papers

Papers	Institutes
16	Lanzhou University, Lanzhou, China
15	University of Iowa, Iowa City, United States
12	Central South University China, Changsha, China
10	Huazhong University of Science and Technology, Wuhan, China
9	Danmarks Tekniske Universitet, Lyngby, Denmark
8	Dongbei University of Finance and EcoNomics, Dalian, China
8	Universitat Rostock, Rostock, Germany
7	Aristotle University of Thessaloniki, Thessaloniki, Greece
6	University of Malaya, Kuala Lumpur, Malaysia

The top 3 institutes in this table are from China and US. A further examination of each institute’s publications reveals that the papers from the two Chinese universities focus on the field of **forecasting**,

while papers from the US university focus on the field of **maintenance**.

The scholars that have published more than 5 highly cited papers are listed in Table 3.3.

Table 3.3: Scholars with more than 5 highly cited papers

Papers	Authors
15	Andrew Kusiak (University of Iowa, United States)
14	Jianzhou Wang (Dongbei University of Finance and Economics, China)
12	Hui Liu (Central South University, China)
12	Yanfei Li (Central South University, China)
9	Hongqi Tian (Central South University, China)
6	Chihming Hong (National Kaohsiung Marine University, Taiwan)
6	Haiyang Zheng (University of Iowa, United States)
6	Zhe Song (Nanjing University, China)

Note that only the latest affiliated institute associated with each author is shown in parentheses. There seems to be some mismatch between these two tables, which can be explained by changing of affiliated institute for some scholars. For example, Jianzhou Wang was affiliated with Lanzhou University but later with Dongbei University of Finance and Economics.

Based on the above literature analysis, we can conclude that:

- AI4Wind has been studied in various application fields
- Among different fields, **forecasting** is the most intensively and successfully researched
- **Control**, **system** and **maintenance** also show significant potentials for AI applications
- ANN is the most widely used AI/ML technique

3.2 Industrial stories

To better demonstrate the state of the art of AI4Wind, two industrial stories of successfully applying AI in wind energy field are described here.

The first story is in the field of **forecasting**.

In 2014, smart wind and solar power was chosen by *MIT Technology Review* as one of the “10 Breakthrough Technologies”. The journal described the breakthrough with the case of [Xcel Energy](#) and National Center for Atmospheric Research (NCAR) in an [article](#) (Bullis [2014]), which said:

Xcel’s original forecasts used data from just one or two weather stations per wind farm. Now NCAR collects information from nearly every wind turbine. The data feeds into a high-resolution weather model and is combined with the output from five additional wind forecasts. Using historical data, NCAR’s software learns which forecasts are best for each wind farm and assigns different weights to each accordingly. The resulting über-forecast is more accurate than any of the original ones. Then, using data about how much power each turbine in the field will generate in response to different wind speeds, NCAR tells Xcel how much power to expect, in 15-minute increments, for up to seven days.

An illustration of 3 days ahead forecasting is shown in Fig. 3.6. In this figure, red lines represent 3 day ahead forecast of wind power, green line is the actual power output, and yellow zones represent the estimated uncertainty of forecasts.

Power Forecast

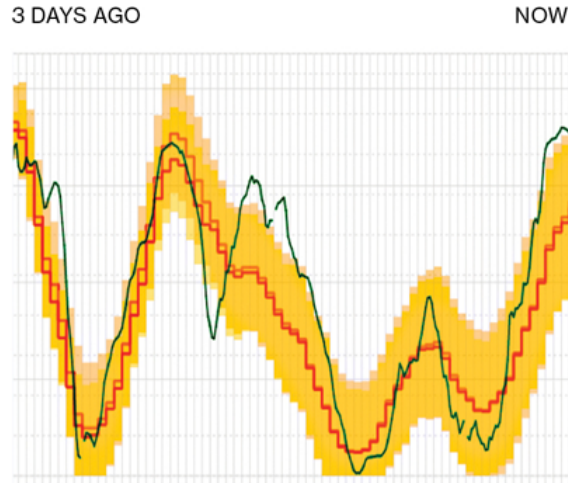


Figure 3.6: Three days ahead power forecasting, source: [Xcel Energy](#)

As Fig. 3.6 shows, companies like Xcel Energy can forecast the power output of a given wind farm 3 days ahead with quite good accuracy. This kind of accuracy is only possible by combining large amount of data (big data) with mature AI techniques such as ANN.

Accurate forecast of wind power output is also essential for increasing the penetration level of wind power in the electrical system, as dealing with the intermittency of wind power naturally requires accurate and reliable forecast. As stated in the [article](#) in *MIT Technology Review* (Bullis [2014]):

The forecasts are helping power companies deal with one of the biggest challenges of wind power: its intermittency. Using small amounts of wind power is no problem for utilities. They are accustomed to dealing with variability—after all, demand for electricity changes from season to season, even from minute to minute. However, a utility that wants to use a lot of wind power needs backup power to protect against a sudden loss of wind. These backup plants, which typically burn fossil fuels, are expensive and dirty. But with more accurate forecasts, utilities can cut the amount of power that needs to be held in reserve, minimizing their role.

Considering the dominance of research in **forecasting** in the literature, as analyzed in the previous sub-section, we can expect that AI will play an even larger role in wind power forecasting and bring successful stories to many other companies as to Xcel Energy.

The second story is from the field of **maintenance**.

Paul Dvorak wrote about an industrial story of applying AI in wind farm O&M in an article published on *Windpower Engineering and Development* in 2018 (Dvorak [2018]). This story is based on the case from [Ensemble Energy](#), an advanced data analytics company dedicated to improving the way that energy is created.

In this article, the conventional O&M's shortcomings are listed as follows:

- **Reactive:** maintenance actions are taken in response to faults or failures.
- **Static:** turbine behaviors have fixed upper and lower fault limits, which are not situation dependent, and are not customized to the known behavior of each turbine.
- **Labor intensive:** developing and running SCADA queries takes many hours of time which strain resources. Useful insights in the data are overlooked, resulting in lost opportunities to increase production or reduce costs.

On the hand, the AI based O&M will have the following advantages:

- **Predictive:** anomalies will be identified in early stages and addressed before faults or failures occur.
- **Dynamic:** turbines will have dynamic fault limits that will be situation dependent and can be customized for each turbine.
- **Automated:** a machine learning platform continually analyzes data in the background, and provides automated notifications to operators, along with suggestions for the most effective corrective actions. Skilled human operators will be freed from tedious data analyses, and their time will be spent on higher value activities.

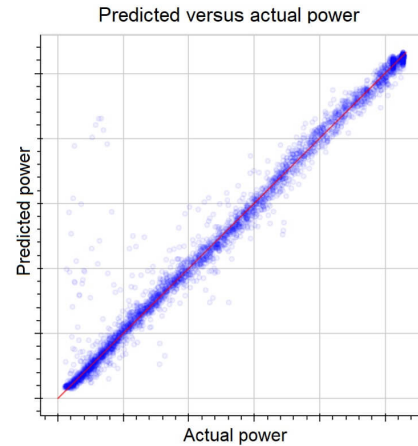
Successful examples of using AI for wind farm O&M described in this article (Dvorak [2018]) include:

- **Detect premature failure of pitch bearings:** a model of expected pitch-bearing behavior under all operating conditions.
- **Detect lubrication anomaly:** a combination of expertise in wind-turbine loads, bearing operation and lubrication, and advanced data analysis.
- **Detect underperforming turbines:** unique ML based power 'curve' created for each individual turbine, including factors beside wind speed, such as: site elevation, seasonal factors, wind shear, turbulence intensity, and more.

Two figures demonstrating two of the AI based wind farm O&M cases are copied here in Fig. 3.7.



(a) Main bearing failed due to insufficient lubrication



(b) Anomaly detection by individual power curve established by ML platform

Figure 3.7: AI based O&M applications in [Ensemble Energy](#), source: Dvorak [2018]

Besides the highly cited AI4Wind papers analyzed here and the industrial stories described above, there are of course many other studies and cases that are worthy of examination. Apparently, no state of the art review can be truly comprehensive and complete, as there are always limits in terms of time and resource, and also one's knowledge of the field. Thus, the literature and cases included in this chapter are limited to gain a general understanding of the current state of the art in AI4Wind in the scope of this study.

Chapter 4

AI4Wind: the prospects and challenges

AI has demonstrated its potential for various wind energy applications, both in numerous published literature and in successful industrial cases. After reflecting on the big picture of AI and examining the state of the art of AI for wind energy, the future prospects and challenges for using AI in wind energy are identified in this chapter.

First of all, will AI bring transformational changes or only incremental improvements to the wind energy sector? To answer this question one needs to first have a realistic assessment of the potential of AI in different wind energy application fields.

Based on the state of the art reviewed in Chapter 3, one can conclude that AI holds great potentials in providing smarter wind turbine/farm controller, better wind power forecasting, lower O&M cost, and maybe also superior wind turbine/farm design. However, all of these improvements, while crucial for further reducing the LCOE (levelized cost of energy) of wind energy, are not likely to revolutionize the whole wind energy sector.

Daniel Bennett from [Entura](#) (a leading power and water consulting company in Australia) came to a similar conclusion in an article entitled with “Can big data and artificial intelligence transform the wind sector?” (Bennett [2017]):

The improvements from applications of machine learning are fascinating for the technically inclined, and are already improving the performance of wind farms worldwide. However, we don't consider them transformational when compared with the major changes the application of AI will have in other industries such as transportation (e.g. self-driving cars). Big data, machine learning and artificial intelligence offer current and future benefits for wind farm developers, manufacturers, owners and electricity market operators and traders, and it's worth considering the applications, while understanding the limitations.

Although AI is not likely to bring transformational changes to the wind energy sector, it is definitely going to be one of the core enabling technologies for our future energy system. This system is going to be cleaner, smarter and cheaper, as:

- power from renewable sources takes a larger share of the world's energy mix;
- technologies such as Internet of Things (IoTs) and 5G enable the online monitoring and controlling of nearly all equipment involved in energy generation, transmission and consumption;
- distributed power generations, electrical vehicles, and smart metering and appliances make the conventional consumers of energy to more active prosumers of energy;
- and the coming energy system thus becomes nearly impossible to operate, dispatch and control using the conventional techniques.

Nevertheless, assessing AI's potential for the future energy system is beyond the scope of this report. Therefore, only the prospects and challenges identified for AI4Wind will be listed here.

Prospects of AI4Wind:

1. **forecasting:** combining different data sources, such as historical power data, power data from neighbouring wind farms and weather forecasting data, and using different AI/ML techniques, the accuracy of wind power can be further improved.
2. **Control:** AI can contribute to model state estimation, data driven model building, parameter tuning, and many other aspects of wind turbine and wind farm control.
3. **O&M:** better condition monitoring, fault detection, prognosis and diagnosis of component or turbine failure, remaining life time estimation and operation and maintenance strategy optimization, etc. with help of AI can largely reduce the O&M cost.
4. **Planning and siting:** AI could help with better wind resource assessment, wind farm site selection, faster project approval and siting of turbines.
5. **System operation and integration:** AI can play an essential role in integrating more wind power into the electrical grid, and also in the operation, dispatch and control of the electrical system with more power from intermittent power sources such as wind and solar.
6. **Design:** AI can complement the high-fidelity numerical model used in the design of wind turbine and turbine component, by providing fast surrogate models based on AI's strength in A to B mapping, which will then enable the optimization of wind turbine design with more design variables and constraints in a shorter time. AI driven optimization methods will also play an important role for finding better designs of wind turbines and wind farms.

Challenges of AI4Wind:

1. **Lack of open data:** as shown in Fig. 2.10, data is the fuel of the AI rocket. In the wind energy sector, data is abundant and will become more so. But it is usually owned and possessed by different stakeholders such as the turbine manufacturers, wind farm developers, wind farm owners, and O&M service providers. The lack of data open to researchers and innovators is likely to slow down the development of AI solutions to wind energy applications. This challenge has also been addressed by Andrew Kusiak in an article published in *Nature* in 2016 (Kusiak [2016]).
2. **Lack of AI expertise:** the success of AI4Wind requires researchers and innovators who have expertise in both AI and wind energy, but the current practitioners in wind energy sectors typically lack sufficient AI expertise. This however can be largely solved by retraining and recruiting.
3. **Lack of explainability:** as explained in sub-section 2.5, the lack of explainability poses a serious challenge when trying to apply AI in some critical application fields. While not so serious as other field such as health, it will also bring certain challenges for the wind energy sector to welcome the use of AI in various application fields.
4. **Cybersecurity:** as AI plays a more central role in the operation, maintenance and control of wind farms and other energy infrastructures, cybersecurity will become an increasingly crucial challenge. This will require more research in the cybersecurity of energy system using AI, and also more robust design of wind farms and energy infrastructures that are more resilient against potential cyber attacks. In general, cybersecurity will be a more crucial challenge when AI is used more deeply and widely in the world.

Chapter 5

Conclusions

AI is coming. Thanks to cheap parallel computation, big data and better algorithms, the true potential of AI is likely to be unleashed across various sectors of business and society in our world (Kelly [2014]). In the near future, we will witness the further penetration of AI as a core enabling technology in different fields. The wind energy sector is not an exception to this trend.

As the review of the state of the art in AI4Wind (Artificial Intelligence for wind energy) has shown, AI has demonstrated its effectiveness and potential in various application fields of wind energy, including wind power forecasting, wind turbine and wind farm control, O&M, etc.. Thousands of papers investigating all kinds of AI4Wind applications have been published, among which some have been very highly cited and produced large impact.

Many companies have also successfully used AI for different purposes in the wind energy industry, and more companies are coming to the playground. These companies will include not only traditional players in the wind energy sector, such as turbine manufacturers and wind farm developers, who aim to use AI to improve their wind turbines or wind farms, but also new players such as large tech companies and new start ups, who use AI as their core competence to solve the application problems in wind energy.

Although AI might not be able to revolutionize the wind energy sector (as discussed in Chapter 4), its ability to bring incremental improvements in various aspects of wind energy will be too important to miss for any serious players in this field. Any companies who want to stay competent in the wind energy sector will have to adopt AI in their research and development efforts.

For wind energy researchers in the academia, the opportunities brought by AI also can't be overlooked. To fully unleash the potential of AI for wind energy, more research will be needed, for which new knowledge and skills need to be learned, conventional work flow and knowledge need to be reconsidered. The success of AI4Wind research can't be realized without collaborative teams of talented researchers, who have in-depth domain knowledge of wind energy, applicable expertise in AI, and above all open and innovative mindsets.

Successful collaborations between companies across the value chain and between academia and industry will also be a prerequisite for the successful application of AI in wind energy. For example, one of the biggest challenges facing AI4Wind, lack of open data, can't be solved by academia alone, and will require innovations in protecting, sharing and exchanging of valuable data.

While the potential of AI4Wind is tremendous, the related challenges are also unneglectable, thus the future of AI4Wind is far from certain. But as the quote, often credited to Abraham Lincoln, says: *"The best way to predict the future is to create it."* It is up to us, the practitioners in wind energy, to determine how well the wind energy sector will harness the potential of AI, so let's work for a brighter future for AI4Wind!

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Appendix

In this Appendix, the detailed list of the focused papers on AI4Wind is presented. These papers are selected based on the citation statistics in Scopus as extracted on March 21, 2018. The search is done by a Python script using API provided by Scopus. The main criterions for selecting these papers are shown in Table A.1.

Table A.1: Criterions for focused papers on AI4Wind

Papers on AI4Wind (based on Scopus search through API @ Mar 21, 2018)	
Criterion	Title(wind) and Title-Abs-Key(intelligence or neural or ANN or AI or learning or data mining or big data)
Total	4172 (there are false positive and false negative)
Highly cited	288 (≥ 5 citations per year since publication according to Scopus)

Note that the citations per year for a paper is calculated by dividing the total citations in Scopus until Mar 21, 2018 and divided by the number of years it has been published until the same date, with number of months accounted, i.e., one month is taken as 1/12 year.

The analysis of these paper has been done in Chapter 3.

In the following list, the 288 focused papers are ranked according to the citation number per year ('citation per y') for each paper. The listed information includes:

- **#**, ranking
- **Title**, title of the paper
- **Year**, publication year
- **Source**, journal or conference it published in
- **Cited**, total citations it received according to Scopus until March 21, 2018
- **Cited per y**, citations per year it received according to Scopus until March 21, 2018
- **Field**, field of the main topic in this paper (**C**: control; **F**: forecasting; **M**: maintenance; **P**: planning; **S**: system; **O**: Others; **R**: Review)

It is worthy to emphasize again that the focused papers are selected based on citation statistics as retrieved from Scopus on March 21, 2018. The same set of criterions if applied to more updated statistics will likely give different results.

#	Title	Year	Source	Cited	Cited per y	Field
1	Current methods and advances in forecasting of wind power generation	2012	Renewable Energy	414	66.24	R
2	A review on the forecasting of wind speed and generated power	2009	Renewable and Sustainable Energy Reviews	462	49.95	R
3	Optimal energy storage sizing and control for wind power applications	2011	IEEE Transactions on Sustainable Energy	254	35.03	C
4	Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model	2012	Renewable Energy	201	32.16	F
5	Probabilistic forecasting of wind power generation using extreme learning machine	2014	IEEE Transactions on Power Systems	133	31.29	F
6	On comparing three artificial neural networks for wind speed forecasting	2010	Applied Energy	255	30.91	F
7	Review of state of the art in smart rotor control research for wind turbines	2010	Progress in Aerospace Sciences	238	28.85	R
8	An advanced statistical method for wind power forecasting	2007	IEEE Transactions on Power Systems	321	28.53	F
9	Short-term load and wind power forecasting using neural network-based prediction intervals	2014	IEEE Transactions on Neural Networks and Learning	120	28.24	F
10	Optimal parameters selection for BP neural network based on particle swarm optimization: A case study of wind speed forecasting	2014	Knowledge-Based Systems	119	28.00	F
11	Support vector machines for wind speed prediction	2004	Renewable Energy	386	27.09	F
12	A review of wind power and wind speed forecasting methods with different time horizons	2010	North American Power Symposium 2010, NAPS 2010	223	27.03	R
13	Wind speed and generated power forecasting in wind farm	2005	Zhongguo Dianji Gongcheng Xuebao/Proceedings of the Chinese Society of Electrical	349	26.34	F
14	The prediction and diagnosis of wind turbine faults	2011	Renewable Energy	184	25.38	M
15	Wind speed forecasting based on the hybrid ensemble empirical mode decomposition and GA-BP neural network method	2016	Renewable Energy	53	23.56	F
16	Long-term wind speed and power forecasting using local recurrent neural network models	2006	IEEE Transactions on Energy Conversion	280	22.86	F
17	A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation	2004	IEEE Transactions on Energy Conversion	312	21.89	F
18	AWNN-Assisted wind power forecasting using feed-forward neural network	2012	IEEE Transactions on Sustainable Energy	135	21.60	F
19	A stochastic model for the optimal operation of a wind-thermal power system	2009	IEEE Transactions on Power Systems	197	21.30	S

#	Title	Year	Source	Cited	Cited per y	Field
20	Wind power forecast using wavelet neural network trained by improved Clonal selection algorithm	2015	Energy Conversion and Management	69	21.23	F
21	Comparison of two new ARIMA-ANN and ARIMA-Kalman hybrid methods for wind speed prediction	2012	Applied Energy	132	21.12	F
22	Optimal allocation and sizing of PV/Wind/Split-diesel/Battery hybrid energy system for minimizing life cycle cost, carbon emission and dump energy of remote residential building	2016	Applied Energy	47	20.89	S
23	Short-term prediction of wind farm power: A data mining approach	2009	IEEE Transactions on Energy Conversion	190	20.54	F
24	Dynamic economic dispatch considering wind power penetration based on wind speed forecasting and stochastic programming	2009	Zhongguo Dianji Gongcheng Xuebao/Proceedings of the Chinese Society of Electrical	189	20.43	S
25	Forecasting models for wind speed using wavelet, wavelet packet, time series and Artificial Neural Networks	2013	Applied Energy	103	19.62	F
26	Condition based maintenance optimization for wind power generation systems under continuous monitoring	2011	Renewable Energy	137	18.90	M
27	Short-term wind speed prediction using an unscented Kalman filter based state-space support vector regression approach	2014	Applied Energy	80	18.82	F
28	Wind speed forecasting based on wavelet packet decomposition and artificial neural networks trained by crisscross optimization algorithm	2016	Energy Conversion and Management	42	18.67	F
29	Short-term wind power forecasting in Portugal by neural networks and wavelet transform	2011	Renewable Energy	134	18.48	F
30	Short term wind speed forecasting in La Venta, Oaxaca, México, using artificial neural networks	2009	Renewable Energy	164	17.73	F
31	Wind power forecasts using gaussian processes and numerical weather prediction	2014	IEEE Transactions on Power Systems	75	17.65	F
32	Optimal prediction intervals of wind power generation	2014	IEEE Transactions on Power	75	17.65	F
33	Wind power prediction based on artificial neural network	2008	Zhongguo Dianji Gongcheng Xuebao/Proceedings of the Chinese Society of Electrical	174	16.98	F
34	A model-free approach to wind farm control using game theoretic methods	2013	IEEE Transactions on Control Systems Technology	88	16.76	C

#	Title	Year	Source	Cited	Cited per y	Field
35	Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal	2011	IEEE Transactions on Sustainable Energy	121	16.69	F
36	Neural MPPT control of wind generators with induction machines without speed sensors	2011	IEEE Transactions on Industrial Electronics	119	16.41	C
37	Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 1: System description	2013	Applied Soft Computing Journal	83	15.81	M
38	Power System stability control for a wind farm based on adaptive dynamic programming	2015	IEEE Transactions on Smart Grid	51	15.69	C
39	A comparative study of empirical mode decomposition-based short-term wind speed forecasting methods	2015	IEEE Transactions on Sustainable Energy	51	15.69	F
40	Probabilistic energy and operation management of a microgrid containing wind/photovoltaic/fuel cell generation and energy storage devices based on point estimate method and self-adaptive gravitational search algorithm	2012	Energy	98	15.68	S
41	Prediction intervals for short-term wind farm power generation forecasts	2013	IEEE Transactions on Sustainable Energy	81	15.43	F
42	Probabilistic multiobjective wind-thermal economic emission dispatch based on point estimated method	2012	Energy	95	15.20	S
43	Transfer learning for short-term wind speed prediction with deep neural networks	2016	Renewable Energy	34	15.11	F
44	Application of artificial neural networks for the wind speed prediction of target station using reference stations data	2007	Renewable Energy	170	15.11	F
45	Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA-ANN model	2010	Renewable Energy	124	15.03	F
46	Expert energy management of a micro-grid considering wind energy uncertainty	2014	Energy Conversion and Management	63	14.82	S
47	Forecasting the wind generation using a two-stage network based on meteorological information	2009	IEEE Transactions on Energy Conversion	137	14.81	F
48	Wind speed forecasting approach using secondary decomposition algorithm and Elman neural networks	2015	Applied Energy	48	14.77	F
49	Bayesian adaptive combination of short-term wind speed forecasts from neural network models	2011	Renewable Energy	107	14.76	F
50	A new strategy for wind speed forecasting using artificial intelligent methods	2009	Renewable Energy	136	14.70	F

#	Title	Year	Source	Cited	Cited per y	Field
51	A combined model based on CEEMDAN and modified flower pollination algorithm for wind speed forecasting	2017	Energy Conversion and Management	18	14.40	F
52	Improved gravitational search algorithm for unit commitment considering uncertainty of wind power	2014	Energy	61	14.35	S
53	Neural-network-based sensorless maximum wind energy capture with compensated power coefficient	2005	IEEE Transactions on Industry Applications	188	14.19	C
54	An integration of ANN wind power estimation into unit commitment considering the forecasting uncertainty	2007	IEEE Transactions on Industry Applications	159	14.13	S
55	A hybrid model for wind speed prediction using empirical mode decomposition and artificial neural networks	2012	Renewable Energy	88	14.08	S
56	A case study on a hybrid wind speed forecasting method using BP neural network	2011	Knowledge-Based Systems	101	13.93	F
57	Forecasting wind speed using empirical mode decomposition and Elman neural network	2014	Applied Soft Computing Journal	59	13.88	F
58	A comparison of various forecasting techniques applied to mean hourly wind speed time series	2000	Renewable Energy	253	13.86	F
59	Daily wind speed forecasting through hybrid KF-ANN model based on ARIMA	2015	Renewable Energy	45	13.85	F
60	A new fuzzy-based combined prediction interval for wind power forecasting	2016	IEEE Transactions on Power Systems	31	13.78	F
61	Prediction, operations, and condition monitoring in wind energy	2013	Energy	72	13.71	R
62	Coordinated reactive power control of a large wind farm and a STATCOM using heuristic dynamic programming	2009	IEEE Transactions on Energy Conversion	126	13.62	C
63	Short-term forecasting of wind speed and related electrical power	1998	Solar Energy	273	13.48	F
64	Pitch angle control in wind turbines above the rated wind speed by multi-layer perceptron and radial basis function neural networks	2009	Expert Systems with Applications	124	13.41	C
65	Wind power prediction by a new forecast engine composed of modified hybrid neural network and enhanced particle swarm optimization	2011	IEEE Transactions on Sustainable Energy	97	13.38	F
66	Analysis of wind power generation and prediction using ANN: A case study	2008	Renewable Energy	137	13.37	F
67	Linear and non-linear autoregressive models for short-term wind speed forecasting	2016	Energy Conversion and Management	30	13.33	F
68	GA based frequency controller for solar thermal-diesel-wind hybrid energy generation/energy storage system	2012	International Journal of Electrical Power and Energy	83	13.28	C

#	Title	Year	Source	Cited	Cited per y	Field
69	Error analysis of short term wind power prediction models	2011	Applied Energy	96	13.24	F
70	Wind power forecasting using advanced neural networks models	1996	IEEE Transactions on Energy Conversion	294	13.21	F
71	The application of artificial neural networks to mapping of wind speed profile for energy application in Nigeria	2010	Applied Energy	109	13.21	P
72	An efficient scenario-based and fuzzy self-adaptive learning particle swarm optimization approach for dynamic economic emission dispatch considering load and wind power uncertainties	2013	Energy	69	13.14	S
73	Very short-term wind speed prediction: A new artificial neural network-Markov chain model	2011	Energy Conversion and Management	94	12.97	F
74	Comparison of new hybrid FEEMD-MLP, FEEMD-ANFIS, Wavelet Packet-MLP and Wavelet Packet-ANFIS for wind speed predictions	2015	Energy Conversion and Management	42	12.92	F
75	Comparison of four Adaboost algorithm based artificial neural networks in wind speed predictions	2015	Energy Conversion and Management	42	12.92	F
76	Using neural networks to estimate wind turbine power generation	2001	IEEE Transactions on Energy Conversion	222	12.87	F
77	Short term wind speed prediction based on evolutionary support vector regression algorithms	2011	Expert Systems with Applications	93	12.83	F
78	Analyzing wind turbine directional behavior: SCADA data mining techniques for efficiency and power assessment	2017	Applied Energy	16	12.80	M
79	GIS-based environmental assessment of wind energy systems for spatial planning: A case study from Western Turkey	2010	Renewable and Sustainable Energy Reviews	105	12.73	P
80	Comparative study of artificial intelligence techniques for sizing of a hydrogen-based stand-alone photovoltaic/wind hybrid system	2014	International Journal of Hydrogen Energy	54	12.71	S
81	Fault diagnosis for a wind turbine transmission system based on manifold learning and Shannon wavelet support vector machine	2014	Renewable Energy	53	12.47	M
82	Current status of wind energy forecasting and a hybrid method for hourly predictions	2016	Energy Conversion and Management	28	12.44	R
83	Time series prediction using artificial wavelet neural network and multi-resolution analysis: Application to wind speed data	2016	Renewable Energy	28	12.44	F
84	Probabilistic constrained load flow considering integration of wind power generation and electric vehicles	2009	IEEE Transactions on Power Systems	115	12.43	S

#	Title	Year	Source	Cited	Cited per y	Field
85	Multi-objective economic emission load dispatch solution using gravitational search algorithm and considering wind power penetration	2013	International Journal of Electrical Power and Energy	65	12.38	S
86	Wind Power Ramp Event Forecasting Using a Stochastic Scenario Generation Method	2015	IEEE Transactions on Sustainable Energy	40	12.31	F
87	Short-term wind power prediction based on LSSVM-GSA model	2015	Energy Conversion and Management	40	12.31	F
88	Intelligent approach to maximum power point tracking control strategy for variable-speed wind turbine generation system	2010	Energy	101	12.24	C
89	Wind speed and rotor position sensorless control for direct-drive PMG wind turbines	2012	IEEE Transactions on Industry Applications	76	12.16	C
90	Four wind speed multi-step forecasting models using extreme learning machines and signal decomposing algorithms	2015	Energy Conversion and Management	39	12.00	F
91	Comparison of two new intelligent wind speed forecasting approaches based on Wavelet Packet Decomposition, Complete Ensemble Empirical Mode Decomposition with Adaptive Noise and Artificial Neural Networks	2018	Energy Conversion and Management	3	12.00	F
92	Deep learning based ensemble approach for probabilistic wind power forecasting	2017	Applied Energy	15	12.00	F
93	Probabilistic wind power forecasting using radial basis function neural networks	2012	IEEE Transactions on Power Systems	75	12.00	F
94	Feature selection in wind speed prediction systems based on a hybrid coral reefs optimization - Extreme learning machine approach	2014	Energy Conversion and Management	51	12.00	F
95	Reactive power control of grid-connected wind farm based on adaptive dynamic programming	2014	Neurocomputing	51	12.00	C
96	A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system	2017	Energy Conversion and Management	15	12.00	R
97	Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection	2011	Mechanical Systems and Signal Processing	86	11.86	M
98	A literature review of wind forecasting technology in the world	2007	2007 IEEE Lausanne POWERTECH, Proceedings	132	11.73	R
99	New wind speed forecasting approaches using fast ensemble empirical model decomposition, genetic algorithm, Mind Evolutionary Algorithm and Artificial Neural Networks	2015	Renewable Energy	38	11.69	F

#	Title	Year	Source	Cited	Cited per y	Field
100	A novel application of an analog ensemble for short-term wind power forecasting	2015	Renewable Energy	38	11.69	F
101	Using data-mining approaches for wind turbine power curve monitoring: A comparative study	2013	IEEE Transactions on Sustainable Energy	61	11.62	O
102	Evaluation of hybrid forecasting approaches for wind speed and power generation time series	2012	Renewable and Sustainable Energy Reviews	72	11.52	F
103	Designing an adaptive fuzzy controller for maximum wind energy extraction	2008	IEEE Transactions on Energy Conversion	118	11.51	C
104	A robust combination approach for short-term wind speed forecasting and analysis - Combination of the ARIMA (Autoregressive Integrated Moving Average), ELM (Extreme Learning Machine), SVM (Support Vector Machine) and LSSVM (Least Square SVM) forecasts using a GPR (Gaussian Process Regression) model	2015	Energy	37	11.38	F
105	A data-driven approach for monitoring blade pitch faults in wind turbines	2011	IEEE Transactions on Sustainable Energy	82	11.31	M
106	Adaptive control of a variable-speed variable-pitch wind turbine using radial-basis function neural network	2013	IEEE Transactions on Control Systems Technology	59	11.24	C
107	A knowledge-based approach for control of two-level energy storage for wind energy systems	2009	IEEE Transactions on Energy Conversion	102	11.03	C
108	Optimization of wind turbine energy and power factor with an evolutionary computation algorithm	2010	Energy	90	10.91	C
109	Estimation of wind speed profile using adaptive neuro-fuzzy inference system (ANFIS)	2011	Applied Energy	79	10.90	F
110	Multi-objective probabilistic distribution feeder reconfiguration considering wind power plants	2014	International Journal of Electrical Power and Energy	46	10.82	O
111	Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction	2009	Renewable Energy	100	10.81	F
112	Data mining and wind power prediction: A literature review	2012	Renewable Energy	67	10.72	R
113	Analyzing bearing faults in wind turbines: A data-mining approach	2012	Renewable Energy	67	10.72	M
114	Wind speed and power forecasting based on spatial correlation models	1999	IEEE Transactions on Energy Conversion	206	10.70	F

#	Title	Year	Source	Cited	Cited per y	Field
115	Deterministic and probabilistic interval prediction for short-term wind power generation based on variational mode decomposition and machine learning methods	2016	Energy Conversion and Management	24	10.67	F
116	Short-term wind speed forecasting based on a hybrid model	2013	Applied Soft Computing	56	10.67	F
117	Locally recurrent neural networks for wind speed prediction using spatial correlation	2007	Information Sciences	120	10.67	F
118	Long-term wind speed forecasting and general pattern recognition using neural networks	2014	IEEE Transactions on Sustainable Energy	45	10.59	F
119	Forecasting wind with neural networks	2003	Marine Structures	160	10.49	F
120	Comparison of two new short-term wind-power forecasting systems	2009	Renewable Energy	97	10.49	F
121	Application of RBF neural networks and unscented transformation in probabilistic power-flow of microgrids including correlated wind/PV units and plug-in hybrid electric vehicles	2017	Simulation Modelling Practice and Theory	13	10.40	O
122	Wind speed forecasting in the South Coast of Oaxaca, México	2007	Renewable Energy	117	10.40	F
123	Modeling wind-turbine power curve: A data partitioning and mining approach	2017	Renewable Energy	13	10.40	O
124	On damage diagnosis for a wind turbine blade using pattern recognition	2014	Journal of Sound and Vibration	44	10.35	M
125	Advanced algorithms for wind turbine power curve modeling	2013	IEEE Transactions on Sustainable Energy	54	10.29	O
126	Models for monitoring wind farm power	2009	Renewable Energy	95	10.27	M
127	Entropy and correntropy against minimum square error in offline and online three-day ahead wind power forecasting	2009	IEEE Transactions on Power Systems	94	10.16	F
128	Size optimization for hybrid photovoltaic-wind energy system using ant colony optimization for continuous domains based integer programming	2015	Applied Soft Computing Journal	33	10.15	S
129	A hybrid pso-anfis approach for short-term wind power prediction in Portugal	2011	Energy Conversion and Management	73	10.07	F
130	Assessment of the benefits of numerical weather predictions in wind power forecasting based on statistical methods	2011	Energy	72	9.93	F
131	Short-term wind power forecasting using ridgelet neural network	2011	Electric Power Systems	72	9.93	F
132	A novel wind power forecast model: Statistical hybrid wind power forecast technique (SHWIP)	2015	IEEE Transactions on Industrial Informatics	32	9.85	F
133	An Adaptive Network-Based Reinforcement Learning Method for MPPT Control of PMSG Wind Energy Conversion Systems	2016	IEEE Transactions on Power Electronics	22	9.78	C

#	Title	Year	Source	Cited	Cited per y	Field
134	A locally recurrent fuzzy neural network with application to the wind speed prediction using spatial correlation	2007	Neurocomputing	109	9.69	F
135	Comparison between wind power prediction models based on wavelet decomposition with Least-Squares Support Vector Machine (LS-SVM) and Artificial Neural Network (ANN)	2014	Energies	41	9.65	F
136	Three-phase AC/DC power-flow for balanced/unbalanced microgrids including wind/solar, droop-controlled and electronically-coupled distributed energy resources using radial basis function neural networks	2017	IET Power Electronics	12	9.60	O
137	A data-driven multi-model methodology with deep feature selection for short-term wind forecasting	2017	Applied Energy	12	9.60	F
138	Design and performance evaluation of a fuzzy-logic-based variable-speed wind generation system	1997	IEEE Transactions on Industry Applications	204	9.60	C
139	A compound structure of ELM based on feature selection and parameter optimization using hybrid backtracking search algorithm for wind speed forecasting	2017	Energy Conversion and Management	12	9.60	F
140	A Coral Reefs Optimization algorithm with Harmony Search operators for accurate wind speed prediction	2015	Renewable Energy	31	9.54	F
141	Optimized control of DFIG-based wind generation using sensitivity analysis and particle swarm optimization	2013	IEEE Transactions on Smart Grid	50	9.52	C
142	Forecasting wind speed with recurrent neural networks	2012	European Journal of Operational Research	59	9.44	F
143	Short-term wind speed forecasting using empirical mode decomposition and feature selection	2016	Renewable Energy	21	9.33	F
144	Application of extreme learning machine for estimation of wind speed distribution	2016	Climate Dynamics	21	9.33	P
145	Predicting the wind power density based upon extreme learning machine	2015	Energy	30	9.23	P
146	Optimal coordinate operation control for wind-photovoltaic-battery storage power-generation units	2015	Energy Conversion and Management	30	9.23	C
147	Fuzzy modeling and optimization algorithm on dynamic economic dispatch in wind power integrated system	2006	Dianli Xitong Zidonghua/Automation of Electric Power Systems	113	9.22	S
148	Adaptive neuro-fuzzy approach for wind turbine power coefficient estimation	2013	Renewable and Sustainable Energy Reviews	48	9.14	C

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149	A new Elman neural network-based control algorithm for adjustable-pitch variable-speed wind-energy conversion systems	2011	IEEE Transactions on Power Electronics	66	9.10	C
150	Multiple architecture system for wind speed prediction	2011	Applied Energy	66	9.10	F
151	Short-term wind speed forecasting with Markov-switching model	2014	Applied Energy	38	8.94	F
152	An SVM-based solution for fault detection in wind turbines	2015	Sensors (Switzerland)	29	8.92	M
153	Wind speed prediction using reduced support vector machines with feature selection	2015	Neurocomputing	29	8.92	F
154	Wind speed prediction in the mountainous region of India using an artificial neural network model	2015	Renewable Energy	29	8.92	F
155	A novel online training neural network-based algorithm for wind speed estimation and adaptive control of PMSG wind turbine system for maximum power extraction	2016	Renewable Energy	20	8.89	C
156	Short-term wind speed and power forecasting using an ensemble of mixture density neural networks	2016	Renewable Energy	20	8.89	F
157	Deep belief network based deterministic and probabilistic wind speed forecasting approach	2016	Applied Energy	20	8.89	F
158	Intelligent and robust prediction of short term wind power using genetic programming based ensemble of neural networks	2017	Energy Conversion and Management	11	8.80	F
159	Monitoring of wind farms' power curves using machine learning	2012	Applied Energy	55	8.80	M
160	A fuzzy controller for maximum energy extraction from variable speed wind power generation systems	2008	Electric Power Systems Research	90	8.78	C
161	Wind farm power prediction: a data-mining approach	2009	Wind Energy	81	8.76	F
162	A new strategy for predicting short-term wind speed using soft computing models	2012	Renewable and Sustainable Energy Reviews	54	8.64	F
163	A self-adaptive hybrid approach for wind speed forecasting	2015	Renewable Energy	28	8.62	F
164	Very short-term wind power forecasting with neural networks and adaptive Bayesian learning	2011	Renewable Energy	62	8.55	F
165	Forecasting wind power in the Mai Liao Wind Farm based on the multi-layer perceptron artificial neural network model with improved simplified swarm optimization	2014	International Journal of Electrical Power and Energy Systems	36	8.47	F
166	Wind speed forecasting using FEEMD echo state networks with RELM in Hebei, China	2016	Energy Conversion and Management	19	8.44	F

#	Title	Year	Source	Cited	Cited per y	Field
167	Optimal design of permanent magnet flux switching generator for wind applications via artificial neural network and multi-objective particle swarm optimization hybrid approach	2016	Energy Conversion and Management	19	8.44	O
168	Load frequency control by neural-network-based integral sliding mode for nonlinear power systems with wind turbines	2016	Neurocomputing	19	8.44	C
169	A hybrid strategy of short term wind power prediction	2013	Renewable Energy	44	8.38	F
170	Combined nonparametric prediction intervals for wind power generation	2013	IEEE Transactions on Sustainable Energy	44	8.38	F
171	Hour-ahead wind power and speed forecasting using simultaneous perturbation stochastic approximation (SPSA) algorithm and neural network with fuzzy inputs	2010	Energy	69	8.36	F
172	Short-term wind power forecasting using evolutionary algorithms for the automated specification of artificial intelligence models	2008	International Journal of Forecasting	84	8.20	F
173	Maximum power point tracking-based control algorithm for PMSG wind generation system without mechanical sensors	2013	Energy Conversion and Management	43	8.19	C
174	Speed control of grid-connected switched reluctance generator driven by variable speed wind turbine using adaptive neural network controller	2012	Electric Power Systems Research	51	8.16	C
175	Recursive wind speed forecasting based on Hammerstein Auto-Regressive model	2015	Applied Energy	26	8.00	F
176	Medium-term wind speeds forecasting utilizing hybrid models for three different sites in Xinjiang, China	2015	Renewable Energy	26	8.00	F
177	Fault analysis and condition monitoring of the wind turbine gearbox	2012	IEEE Transactions on Energy Conversion	50	8.00	M
178	Sparse online warped Gaussian process for wind power probabilistic forecasting	2013	Applied Energy	42	8.00	F
179	Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and Elman neural network	2018	Energy Conversion and Management	2	8.00	F
180	Big multi-step wind speed forecasting model based on secondary decomposition, ensemble method and error correction algorithm	2018	Energy Conversion and Management	2	8.00	F
181	Using artificial neural networks for temporal and spatial wind speed forecasting in Iran	2016	Energy Conversion and Management	18	8.00	F
182	A neural networks approach for wind speed prediction	1998	Renewable Energy	159	7.85	F

#	Title	Year	Source	Cited	Cited per y	Field
183	Short-term wind power ensemble prediction based on gaussian processes and Neural networks	2014	IEEE Transactions on Smart Grid	33	7.76	F
184	Wind power forecasting based on principle component phase space reconstruction	2015	Renewable Energy	25	7.69	F
185	Sensorless control for a switched reluctance wind generator, based on current slopes and neural networks	2009	IEEE Transactions on Industrial Electronics	71	7.68	C
186	Modeling and forecasting the mean hourly wind speed time series using GMDH-based abductive networks	2009	Renewable Energy	71	7.68	F
187	Hybrid technique of ant colony and particle swarm optimization for short term wind energy forecasting	2013	Journal of Wind Engineering and Industrial Aerodynamics	40	7.62	F
188	A generalized model for wind turbine anomaly identification based on SCADA data	2016	Applied Energy	17	7.56	M
189	Intelligent control of a class of wind energy conversion systems	1999	IEEE Transactions on Energy Conversion	145	7.53	C
190	Transient stability enhancement of wind farms connected to a multi-machine power system by using an adaptive ANN-controlled SMES	2014	Energy Conversion and Management	32	7.53	O
191	Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 2: Application examples	2014	Applied Soft Computing Journal	32	7.53	M
192	A data-mining approach to monitoring wind turbines	2012	IEEE Transactions on Sustainable Energy	47	7.52	M
193	Application of a control algorithm for wind speed prediction and active power generation	2005	Renewable Energy	99	7.47	F
194	A novel approach for the forecasting of mean hourly wind speed time series	2002	Renewable Energy	121	7.45	F
195	Estimation methods review and analysis of offshore extreme wind speeds and wind energy resources	2015	Renewable and Sustainable Energy Reviews	24	7.38	P
196	A new self-scheduling strategy for integrated operation of wind and pumped-storage power plants in power markets	2011	Applied Energy	53	7.31	S
197	Extreme learning machine based wind speed estimation and sensorless control for wind turbine power generation system	2013	Neurocomputing	38	7.24	C
198	Agent-based modeling for trading wind power with uncertainty in the day-ahead wholesale electricity markets of single-sided auctions	2012	Applied Energy	45	7.20	S

#	Title	Year	Source	Cited	Cited per y	Field
199	Research and application of a combined model based on multi-objective optimization for multi-step ahead wind speed forecasting	2017	Energy	9	7.20	F
200	Multi-step wind speed forecasting based on a hybrid forecasting architecture and an improved bat algorithm	2017	Energy Conversion and Management	9	7.20	F
201	Design and overview of maximum power point tracking techniques in wind and solar photovoltaic systems: A review	2017	Renewable and Sustainable Energy Reviews	9	7.20	R
202	A novel forecasting model based on a hybrid processing strategy and an optimized local linear fuzzy neural network to make wind power forecasting: A case study of wind farms in China	2017	Renewable Energy	9	7.20	F
203	A variable speed wind generator maximum power tracking based on adaptive neuro-fuzzy inference system	2011	Expert Systems with Applications	52	7.17	C
204	Output power control for variable-speed variable-pitch wind generation systems	2010	IEEE Transactions on Energy Conversion	59	7.15	C
205	Wind speed and solar irradiance forecasting techniques for enhanced renewable energy integration with the grid: A review	2016	IET Renewable Power Generation	16	7.11	R
206	A spatio-temporal analysis approach for short-term forecast of wind farm generation	2014	IEEE Transactions on Power Systems	30	7.06	F
207	Wind speed estimation using multilayer perceptron	2014	Energy Conversion and Management	30	7.06	F
208	Wind power grouping forecasts and its uncertainty analysis using optimized relevance vector machine	2013	Renewable and Sustainable Energy Reviews	37	7.05	F
209	An experimental investigation of two Wavelet-MLP hybrid frameworks for wind speed prediction using GA and PSO optimization	2013	International Journal of Electrical Power and Energy	37	7.05	F
210	Universal tracking control of wind conversion system for purpose of maximum power acquisition under hierarchical control structure	2011	IEEE Transactions on Energy Conversion	51	7.03	C
211	Short-term wind power output forecasting model for economic dispatch of power system incorporating large-scale wind farm	2010	Zhongguo Dianji Gongcheng Xuebao/Proceedings of the Chinese Society of Electrical Engineering	58	7.03	F
212	Prediction of wind farm power ramp rates: A data-mining approach	2009	Journal of Solar Energy Engineering, Transactions of	64	6.92	F
213	Application of quantum-inspired binary gravitational search algorithm for thermal unit commitment with wind power integration	2014	Energy Conversion and Management	29	6.82	S

#	Title	Year	Source	Cited	Cited per y	Field
214	A new wind speed forecasting strategy based on the chaotic time series modelling technique and the Apriori algorithm	2014	Energy Conversion and Management	29	6.82	F
215	Neural network based hybrid computing model for wind speed prediction	2013	Neurocomputing	35	6.67	F
216	Post-processing techniques and principal component analysis for regional wind power and solar irradiance forecasting	2016	Solar Energy	15	6.67	F
217	Direct interval forecasting of wind speed using radial basis function neural networks in a multi-objective optimization framework	2016	Neurocomputing	15	6.67	F
218	Using data-driven approach for wind power prediction: A comparative study	2016	Energy Conversion and Management	15	6.67	F
219	Machine learning ensembles for wind power prediction	2016	Renewable Energy	15	6.67	F
220	A novel bidirectional mechanism based on time series model for wind power forecasting	2016	Applied Energy	15	6.67	F
221	A comparative study between three sensorless control strategies for PMSG in wind energy conversion system	2009	Applied Energy	60	6.49	C
222	Accurate short-term wind speed prediction by exploiting diversity in input data using banks of artificial neural networks	2009	Neurocomputing	60	6.49	F
223	Hybrid intelligent approach for short-term wind power forecasting in Portugal	2011	IET Renewable Power Generation	47	6.48	F
224	Direct interval forecasting of wind power	2013	IEEE Transactions on Power	34	6.48	F
225	Prediction of wind power by chaos and BP artificial neural networks approach based on genetic algorithm	2015	Journal of Electrical Engineering and Technology	21	6.46	F
226	Data mining techniques for performance analysis of onshore wind farms	2015	Applied Energy	21	6.46	M
227	A generalized dynamic fuzzy neural network based on singular spectrum analysis optimized by brain storm optimization for short-term wind speed forecasting	2017	Applied Soft Computing Journal	8	6.40	F
228	A novel hybrid approach for wind speed prediction	2014	Information Sciences	27	6.35	F
229	Optimal operation strategy of energy storage unit in wind power integration based on stochastic programming	2011	IET Renewable Power Generation	46	6.34	S
230	Short-horizon prediction of wind power: A data-driven approach	2010	IEEE Transactions on Energy Conversion	52	6.30	F
231	Kernel ridge regression with active learning for wind speed prediction	2013	Applied Energy	33	6.29	F
232	A hybrid wind power forecasting model based on data mining and wavelets analysis	2016	Energy Conversion and Management	14	6.22	F

#	Title	Year	Source	Cited	Cited per y	Field
233	A Gaussian process regression based hybrid approach for short-term wind speed prediction	2016	Energy Conversion and Management	14	6.22	F
234	Short-term wind power combined forecasting based on error forecast correction	2016	Energy Conversion and Management	14	6.22	F
235	Hybrid model for hourly forecast of photovoltaic and wind power	2013	IEEE International Conference on Fuzzy Systems	32	6.10	F
236	RBF neural network based PI pitch controller for a class of 5-MW wind turbines using particle swarm optimization algorithm.	2012	ISA transactions	38	6.08	C
237	Performance evaluation and accuracy enhancement of a day-ahead wind power forecasting system in China	2012	Renewable Energy	38	6.08	F
238	Short-term forecasting of wind power and non-parametric confidence interval estimation	2011	Zhongguo Dianji Gongcheng Xuebao/Proceedings of the Chinese Society of Electrical	44	6.07	F
239	A short-term wind power prediction method based on wavelet decomposition and BP neural network	2011	Dianli Xitong Zidonghua/Automation of Electric Power Systems	44	6.07	F
240	Locally recurrent neural networks for long-term wind speed and power prediction	2006	Neurocomputing	74	6.04	F
241	Wind tunnel testing of a smart rotor model with trailing-edge flaps	2002	Journal of the American Helicopter Society	98	6.03	C
242	Hybrid intelligent control of PMSG wind generation system using pitch angle control with RBFN	2011	Energy Conversion and Management	43	5.93	C
243	Intelligent control of a grid-connected wind-photovoltaic hybrid power systems	2014	International Journal of Electrical Power and Energy	25	5.88	C
244	Interval forecasts of a novelty hybrid model for wind speeds	2015	Energy Reports	19	5.85	F
245	A review of estimation of effective wind speed based control of wind turbines	2015	Renewable and Sustainable Energy Reviews	19	5.85	R
246	A Pareto optimal multi-objective optimization for a horizontal axis wind turbine blade airfoil sections utilizing exergy analysis and neural networks	2015	Journal of Wind Engineering and Industrial Aerodynamics	19	5.85	O
247	Application of multi-class fuzzy support vector machine classifier for fault diagnosis of wind turbine	2016	Fuzzy Sets and Systems	13	5.78	M
248	Wind turbine power curve modelling using artificial neural network	2016	Renewable Energy	13	5.78	O

#	Title	Year	Source	Cited	Cited per y	Field
249	Hybrid dynamic classifier for drift-like fault diagnosis in a class of hybrid dynamic systems: Application to wind turbine converters	2016	Neurocomputing	13	5.78	M
250	Analysis and application of forecasting models in wind power integration: A review of multi-step-ahead wind speed forecasting models	2016	Renewable and Sustainable Energy Reviews	13	5.78	R
251	Wind turbine fault diagnosis method based on diagonal spectrum and clustering binary tree SVM	2013	Renewable Energy	30	5.71	M
252	Developing a discrete harmony search algorithm for size optimization of wind-photovoltaic hybrid energy system	2013	Solar Energy	30	5.71	S
253	Power optimization of wind turbines with data mining and evolutionary computation	2010	Renewable Energy	47	5.70	C
254	Dynamic control of wind turbines	2010	Renewable Energy	47	5.70	C
255	Fuzzy neural network output maximization control for sensorless wind energy conversion system	2010	Renewable Energy	47	5.70	C
256	An adaptive neuro-fuzzy inference system approach for prediction of tip speed ratio in wind turbines	2010	Expert Systems with Applications	47	5.70	O
257	A novel hybrid methodology for short-term wind power forecasting based on adaptive neuro-fuzzy inference system	2017	Renewable Energy	7	5.60	F
258	A modified gravitational search algorithm based on a non-dominated sorting genetic approach for hydro-thermal-wind economic emission dispatching	2017	Energy	7	5.60	S
259	An improved neural network-based approach for short-term wind speed and power forecast	2017	Renewable Energy	7	5.60	F
260	Artificial neural network approach to spatial estimation of wind velocity data	2006	Energy Conversion and Management	68	5.55	P
261	Wind Power Forecasting Using Neural Network Ensembles with Feature Selection	2015	IEEE Transactions on Sustainable Energy	18	5.54	F
262	Predictive Deep Boltzmann Machine for Multiperiod Wind Speed Forecasting	2015	IEEE Transactions on Sustainable Energy	18	5.54	F
263	Ultra-short-term wind power forecasting based on SVM optimized by GA	2015	Dianli Xitong Baohu yu Kongzhi/Power System Protection and Control	18	5.54	F
264	Multistage Wind-Electric Power Forecast by Using a Combination of Advanced Statistical Methods	2015	IEEE Transactions on Industrial Informatics	18	5.54	F

#	Title	Year	Source	Cited	Cited per y	Field
265	Generalized adaptive neuro-fuzzy based method for wind speed distribution prediction	2015	Flow Measurement and Instrumentation	18	5.54	F
266	Weighted error functions in artificial neural networks for improved wind energy potential estimation	2013	Applied Energy	29	5.52	P
267	Short-term power prediction of a wind farm based on wavelet analysis	2009	Zhongguo Dianji Gongcheng Xuebao/Proceedings of the Chinese Society of Electrical	51	5.51	P
268	Fault diagnosis of three-parallel voltage-source converter for a high-power wind turbine	2012	IET Power Electronics	34	5.44	M
269	Improving efficiency of two-type maximum power point tracking methods of tip-speed ratio and optimum torque in wind turbine system using a quantum neural network	2014	Energy	23	5.41	C
270	Complex-valued forecasting of wind profile	2006	Renewable Energy	66	5.39	F
271	Use of scada data for failure detection in wind turbines	2011	ASME 2011 5th International Conference on Energy Sustainability, ES 2011	39	5.38	M
272	Short-term wind speed or power forecasting with heteroscedastic support vector regression	2016	IEEE Transactions on Sustainable Energy	12	5.33	F
273	A new intelligent method based on combination of VMD and ELM for short term wind power forecasting	2016	Neurocomputing	12	5.33	F
274	A Survey of Cyber-Physical Advances and Challenges of Wind Energy Conversion Systems: Prospects for Internet of Energy	2016	IEEE Internet of Things Journal	12	5.33	R
275	Wind speed prediction using a univariate ARIMA model and a multivariate NARX model	2016	Energies	12	5.33	F
276	Energy and spinning reserve scheduling for a wind-thermal power system using CMA-ES with mean learning technique	2013	International Journal of Electrical Power and Energy	28	5.33	S
277	Wind power forecasting using fuzzy neural networks enhanced with on-line prediction risk assessment	2003	2003 IEEE Bologna PowerTech - Conference Proceedings	81	5.31	F
278	Wind speed and wind turbine output forecast based on combination method	2009	Dianli Xitong Zidonghua/Automation of Electric Power Systems	49	5.30	F

#	Title	Year	Source	Cited	Cited per y	Field
279	Reduction of frequency fluctuation for wind farm connected power systems by an adaptive artificial neural network controlled energy capacitor system	2012	IET Renewable Power Generation	33	5.28	C
280	An intelligent dynamic security assessment framework for power systems with wind power	2012	IEEE Transactions on Industrial Informatics	33	5.28	S
281	Wind speed spatial estimation for energy planning in Sicily: A neural kriging application	2008	Renewable Energy	54	5.27	P
282	Wind power ramp events classification and forecasting: A data mining approach	2011	IEEE Power and Energy Society General Meeting	38	5.24	F
283	The "Weather intelligence for renewable energies" benchmarking exercise on short-term forecasting of wind and solar power generation	2015	Energies	17	5.23	F
284	How Wind Turbines Alignment to Wind Direction Affects Efficiency? A Case Study through SCADA Data Mining	2015	Energy Procedia	17	5.23	M
285	A novel approach to capture the maximum power from variable speed wind turbines using PI controller, RBF neural network and GSA evolutionary algorithm	2015	Renewable and Sustainable Energy Reviews	17	5.23	C
286	Nonlinear model identification of wind turbine with a neural network	2004	IEEE Transactions on Energy Conversion	74	5.19	O
287	Intelligent optimized wind resource assessment and wind turbines selection in Huitengxile of Inner Mongolia, China	2013	Applied Energy	27	5.14	P
288	Generalized feed-forward based method for wind energy prediction	2013	Applied Energy	27	5.14	P

DTU Wind Energy is a department of the Technical University of Denmark with a unique integration of research, education, innovation and public/private sector consulting in the field of wind energy. Our activities develop new opportunities and technology for the global and Danish exploitation of wind energy. Research focuses on key technical-scientific fields, which are central for the development, innovation and use of wind energy and provides the basis for advanced education at the education.

We have more than 230 employees including more than 150 academics and 40 PhD students from more than 37 different countries. Research is conducted within 10 sections and coordinated and developed via 3 cross-cutting programmes on Siting and Integration, Offshore Wind Energy and Wind Turbine Technology.

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ISBN: 978-87-93549-48-7